The Cost of Fiscal Policy Uncertainty: Industry Evidence of Its Impact on the Labor Market

J. Christina Wang

Abstract:
The anemic pace of the recovery of the U.S. economy from the Great Recession has frequently been blamed on heightened uncertainty, much of which concerns the nation's fiscal policy. Intuition suggests that increased policy uncertainty likely has different impacts on industries with different exposure to government actions. Such heterogeneity can help identify the effect of shocks due to to policy uncertainty. This study uses industry data to explore whether policy uncertainty indeed affects the dynamics of employment during this recovery, and particularly whether it has a differential impact on employment across industries. This analysis focuses on heterogeneity across industries in terms of the fraction of their product demand that can ultimately be attributed to federal government expenditures. The estimation results reveal that policy uncertainty indeed retards employment growth more in industries that rely more heavily on federal government demand: the growth rate in the number of production employees in these industries appears to have been four-tenths of a percentage point lower during the quarters in recent years when policy uncertainty spiked. A similar impact is found for the growth of total employment, which also includes nonproduction employees. In addition, the evidence suggests that increased policy uncertainty renders firms more reluctant to adjust the number of employees in response to changes in output, a contributing factor to the sluggish recovery in employment. Moreover, this damping effect is stronger for industries with higher shares of output sold directly and indirectly to the federal government. By comparison, the adverse effect of heightened policy uncertainty on average weekly hours differs little across industries.

Keywords: uncertainty, fiscal policy, input-output tables, industry accounts, employment, hours
JEL Classifications: D57, D80, E24, E66, G18, L50.

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I would like to thank Susanto Basu, Michelle Barnes, Giovanni Olivei, Ali Ozdagli, and Joe Peek for helpful discussions and comments. Many thanks to Alison Pearson for research assistance, and especially to Vladimir Yankov for exceptional assistance.

This version: January 2014

I. Introduction

The recent government shutdown and nail-biting apprehension about the realistic threat of the U.S. government defaulting on its obligations if the debt ceiling were not raised in time highlighted once again the potential for serious damage to the U.S. economy from heightened uncertainty surrounding the nation's fiscal policy. A growing number of similar previous episodes, such as the debt-ceiling debate over the summer of 2011, the tense "fiscal cliff" debate shortly before the turn of the new year, and the subsequent sequestration, have been blamed for sapping the economy of its precious momentum and contributing to the slow pace of recovery from the Great Recession. The weakness of this recovery, which follows an exceptionally deep recession, has surprised many, and the elevated perception of uncertainty has become a popular target blamed for the slow pace of growth. Much of the uncertainty seems to be focused on government at the federal level and related to the inability of the legislative and the executive branches of the U.S. government to reach consensus on a policy that will achieve long-term fiscal sustainability.

Many existing studies of the effects of uncertainty on economic activity, especially those that rely on a structural approach, such as the use of dynamic stochastic general equilibrium (DSGE) models, focus on the impact of uncertainty on the economy in the aggregate.[1] The merit of the structural approach notwithstanding, one of its potential drawbacks is that any inferences can be sensitive to model assumptions. Therefore, conclusions may be less than robust, or even erroneous, if the simplifying assumptions miss important aspects of reality. To complement those studies, this paper utilizes cross-sectional variation to help identify the impact of uncertainty, without imposing structural restrictions. It relies on the simple premise that cross-sectional heterogeneity in economic units' sensitivity to uncertainty likely leads to disparate effects of uncertainty across households or firms. Possible differential responses to uncertainty shocks in the cross section can stem from either different exposures to the source of the uncertainty or from different adjustment technologies. In this study, the primary emphasis is on uncertainty about fiscal policy. Therefore, the focus will be on the dimension of heterogeneity that is due to differences in the exposure to the source of policy uncertainty.

[1] For example, Basu and Bundick (2012) use a DSGE model with time-varying markups to show that uncertainty shocks lead to declines in consumption, output, and hours. Leduc and Liu (2012) show that an uncertainty shock acts just like an aggregate demand shock—raising unemployment and lowering inflation. Bloom et al. (2012), by comparison, study the impact of uncertainty shocks in a DSGE model with heterogeneous firms.

More specifically, industry data are utilized to focus on how the fraction of industry output eventually purchased by the government sector, particularly the federal government, varies across industries. It seems natural to focus on the federal government, which has been the primary source of recent policy uncertainty. The federal budget deficit and debt have ballooned since the Great Recession because the federal government needed to provide fiscal stimulus, not only to soften the fall in private-sector spending, but also to partly offset steep cuts in state and local government spending. More worrisome than this cyclical swing in the federal deficit and debt is the projected structural shortfall that will only worsen over the next decade or so, if existing policies continue, as more and more baby-boomers retire.

Federal spending is on one side of the fiscal ledger, while taxes are on the other. It is clear that the federal government will have to either cut spending or raise taxes, or both, in order to achieve long-run budget sustainability. However, it is far from clear whether any reduction in the structural component of the federal deficit would occur primarily through spending cuts, tax increases, or a more even blend of the two. This uncertainty clearly affects both sides of the ledger. Since the cross-industry disparity in the importance of government is easier to see in terms of product demand, for which better and more accessible data are available, I focus on the uncertainty concerning government spending for goods and services, rather than on uncertainty about taxation.

The basic logic of the identification strategy used here is that if some firms or industries rely more than others on government purchases, then, all else being equal, the heightened uncertainty concerning fiscal policy should cause those firms or industries to be more cautious than others about adjusting their factor inputs that are subject to adjustment costs. According to Bloom's (2009) influential structural study, the impact of temporary uncertainty shocks is fairly short-lived, so we need relatively high-frequency data on factor inputs. At the industry level, this points to employment, since the data are available monthly and in a timely manner. In contrast, industry-level data on investment are available only at an annual frequency and with a relatively long delay.

We examine whether employment growth was lower in industries that rely more on government demand than in other industries during episodes of heightened fiscal policy uncertainty since the beginning of the Great Recession. It should be noted that the change in employment is a net flow, reflecting the change in hiring net of total separations (due to layoffs, quits, and other reasons). For various reasons that will be explained in detail below, the measured net change in employment is almost surely less sensitive to variations in uncertainty than its gross components would be, at least in theory.

For instance, it is likely that the rates of both hiring and separations slow following an uncertainty shock, in the latter case because workers also become more cautious, and therefore less likely to quit. These two gross flows would then offset each other at least partially, leaving the net change in employment less responsive to uncertainty shocks than its components. In contrast, investment, as a gross flow, is not subject to this attenuation effect. Moreover, investment is subject to greater adjustment costs than employment, and so should react more strongly to exogenous changes in uncertainty. The potential advantage of using industry data, which are limited to employment at a monthly or quarterly frequency, is that these data would constitute stronger evidence for the effect of uncertainty shocks and are more reliable for making inferences about the likely aggregate effect of uncertainty.

Since previous studies have shown that the key determinant of a firm's reaction to unexpected changes in uncertainty is the option value of waiting, we consider two measures of employment that may be subject to different values of this real-options effect for any given degree of uncertainty. One measure counts all employees on the payroll (during each survey period), while the other counts only those classified as production and nonsupervisory workers. As discussed further below, the former may be more sensitive to uncertainty shocks because the option value of waiting (to hire) may be higher concerning workers not directly engaged in current production. For comparison, we also examine how the adjustment dynamic of average weekly hours reacts to exogenous changes in uncertainty. Theory suggests that uncertainty should not affect firms' optimal choice of average hours once it is conditioned on the chosen number of employees, since adjusting average hours is generally understood to incur no cost. As we will show, for various reasons, the difference in the data between employees[2] and average hours, in terms of sensitivity to uncertainty, is not as stark as theory would suggest.

This paper proceeds as follows. Section II explains how an industry's reliance on government demand is defined and summarizes the cross-industry pattern of this measure. It also illustrates the difference in employment dynamics when industries are sorted according to their reliance on federal demand. Section III reviews the theoretical background for why and how uncertainty shocks can affect firms' optimal choice of employment (and investment), and the implications for the regression specifications. Section IV discusses specifications of the panel regressions for employees versus average weekly hours, both with and without controls for each industry's own output growth. Section V reports

[2] We use "employees" mainly to conform to the terminology used by the Bureau of Labor Statistics. In the rest of the paper, we use "employees" interchangeably with "employment," which is more natural for reference to growth rate.

the estimation results, focusing on coefficients related to the measure of policy uncertainty. Section VI concludes.

II. Cross-Industry Heterogeneity of Reliance on Government Final Demand

First, we describe how we measure an industry's exposure to federal government spending and present statistics summarizing the cross-industry variation in this measure. Note that here spending refers to the government's direct final purchases of goods and services produced by the private sector (that is, government consumption expenditures and gross investment in the GDP account), not its outlays that go to pay the wages of government employees who provide government services.[3] By standard definition, government spending also excludes transfer payments to individuals, such as unemployment benefits, social security payments, etc., even though (at least part of) these payments are eventually spent on goods and services.

We define an industry's policy exposure in terms of the share of its output that is accounted for, directly or indirectly, by government purchases. Our intent is to detect whether there have been systematic differences in employment. Our hypothesis is that, all else being equal, during periods of heightened uncertainty regarding the future path of government spending, industries that sell a greater fraction of their output to the federal government are likely to slow hiring more than industries less reliant on federal government purchases. Since times of elevated uncertainty may coincide with times of subdued expectations regarding future growth rates of government spending, we control for the forecast of federal government spending, in order to isolate the effect of uncertainty. For example, the second half of 2012 through early 2013 is perceived to have been a period when the degree of uncertainty concerning future fiscal policy increased as a result of protracted and acrimonious disputes among politicians. Consequently, we would expect industries with a higher share of sales to the federal government to have slowed employment growth during that period more than those industries with a lower share, all else being equal.

To obtain a measure of the amount of an industry's output that is eventually driven by government demand, as opposed to only its direct sales to the government, we make use of the input-output (IO) tables compiled by the Bureau of Economic Analysis (BEA), which summarize the production

[3] Note also that purchases of services by the government on behalf of households, such as medical care purchased under government programs such as Medicare, are counted under personal consumption expenditures (PCE) in the National Income and Product Accounts, not as government expenditures.

structure across industries and the eventual supply to final uses. More specifically, we compute the share of each industry's output that is either sold directly to the federal government or incorporated into products eventually sold directly to the federal government. We do so by combining the information on how many dollars of each industry's output are needed to supply one dollar of final demand for any good or service (provided in the total requirements table) with data on the federal government's final demand for each commodity (provided in the use table), and each industry's total output (provided in the make table).[4] Appendix A offers a more detailed derivation of the total requirements and the share of each industry's output that is ultimately driven by final purchases made by the federal government. The distinction between an industry's ultimate versus direct sales to government stems from the multistage production chain common in modern economies.[5] Thus, every dollar of final demand for any good or service calls for intermediate output by multiple industries in different stages along the production chain. It is intuitive to recognize that the difference between these two measures of industry sales to the government is larger for industries situated earlier in the production chain.[6]

To measure an industry's reliance on federal government demand, and hence its sensitivity to policy uncertainty, we use the industry's total ultimate supply to the federal government to satisfy both defense and nondefense needs. Although future defense spending may be subject to less uncertainty than nondefense spending, no separate measures of uncertainty are available for this. On the other hand, as a measure of exogenous fluctuations in the demand for an industry's product, we use only federal government purchases for defense purposes, weighted by the share of each industry's output that is driven ultimately by defense spending. Including this demand control should yield more consistent coefficient estimates for policy uncertainty, to the extent that greater uncertainty tends to be associated with lower spending, which also dampens employment growth by reducing demand for an industry's output. The coefficient on policy uncertainty alone would, in this case, overstate its impact unless we also control for federal government demand to correct this bias. Note, however, that including endogenous components of government spending, which are likely affected by uncertainty themselves, tends to bias

[4] The use table is essentially a commodity-by-industry matrix where an element (i, j) in row i and column j reports the amount of commodity i used by industry j in producing its output, or consumed as part of a final expenditure item (that is, expenditures in the national income accounts such as government consumption and gross investment). The make table, on the other hand, is an industry-by-commodity matrix where an element (i, j) shows the amount of a given commodity j that is produced in industry i.

[5] A firm or industry that sells directly to the government has to purchase its inputs from other industries, which in turn use as inputs products from industries further upstream in the production chain, and so forth.

[6] The less processed an industry's output (for example, steel sheets versus assembled cars), the greater the number of subsequent steps of production it will traverse before eventually reaching the final user—the federal government in this case.

down the explanatory power of uncertainty. We therefore exclude federal nondefense spending, since it depends on the health of the private sector, which is almost certainly affected by uncertainty. By the same logic, we will also include exports as a demand control, which can be treated as exogenous to the extent that shocks to foreign demand, the primary driver of exports in the short run, are largely uncorrelated with shocks to domestic policy uncertainty. Otherwise, for instance if business cycles are highly synchronized across countries and uncertainty spikes during downturns, including exports will also bias downward the explanatory power of policy uncertainty. As shown below, this may be the case for our specific sample period, during which exports comove rather positively with the U.S. business cycle.

In general, it is not valid to control for product demand using any variable that is itself affected by policy uncertainty, whose impact would thus be underestimated. This argument applies to industry-specific as well as overall cyclical variables. For instance, both industry sales and aggregate output, unlike defense spending, likely already incorporate the influence of policy uncertainty themselves. One known exception is to treat the aggregate variables corresponding to the dependent and the relevant independent variables as controls for unobserved general cross-sectional dependence in a correlated-common-effects (CCE) estimator à la Pesaran (2006). We will apply CCE-type estimators in our analysis to control for cross-industry correlation through an unknown number of common economic factors, while allowing for possible slope heterogeneity in a dynamic panel. In addition, as a robustness check, we will also examine a specification that includes controls for aggregate output (that is, GDP), which will likely lead to an underestimation of the magnitude of the coefficient on policy uncertainty. This estimate can be regarded as close to a lower bound on the effect of policy uncertainty.

First, we present summary statistics of the cross-industry distribution of the share of ultimate sales to the federal government, which uses the purchased goods and services for defense versus nondefense purposes. Table 1 reports the share (in percent) of industry output sold directly and indirectly to satisfy federal *defense* final demand for the top 10 industries in 2002 in descending order.[7] It also presents their shares for a few other select years spanning the sample period over which we have input-output tables compiled by the BEA. There are a total of 59 non-overlapping industries, dictated by the availability of annual input-output tables compiled by the BEA. See Table A.1 in the appendix for the full list of industries (some of which are subsets of others) covered by the BEA's annual input-output tables. The shares span a fairly wide range, from just 3 percent to a little over 30 percent. The ranking, on the

[7] We choose 2002 as the base year because it is the last year for which there are detailed benchmark IO tables available.

other hand, is fairly stable over all these years, especially between 2002 and 2007; most of these industries are ranked among the top 10 in most of the years, with those falling below the top 10 in any given year reported in italics.[8]

Many of the industries on the list are what we would call high-tech (that is, computer-related, information processing) or durable goods industries (for example, transportation equipment, fabricated metal). This is noteworthy because durable goods output tends to be more cyclical than the output of other industries, on average. So if uncertainty shocks were associated with slower aggregate growth, then these industries' growth would be more correlated with heightened uncertainty because of their greater cyclicality, not simply because of their heavier reliance on government purchases. It could thus be argued that one needs to control for the greater cyclicality of these industries in order to uncover accurately the heterogeneous effect of uncertainty. On the other hand, it can also be argued that if increased uncertainty is consistently associated with slower aggregate growth, then it is, in and of itself, supportive evidence for the deleterious effect of uncertainty shocks.

To obtain consistent estimates of the effects of fiscal policy uncertainty on an industry's employment, some of the panel regressions control for the greater cyclicality of those industries with larger shares of output sold to the government. We then explore the resulting difference in the estimated coefficients of interest. One way to control for the different cyclicality is to interact a durable-goods industry dummy variable with total private nonfarm industry employment, when the latter is included as a control for macroeconomic conditions. Alternatively, the two industry-specific exogenous aggregate demand variables (that is, defense spending and exports) explained above can be viewed as a partial control for the different sensitivity to demand shifts across industries.

Table 2 reports the corresponding figures for industry direct and indirect sales for federal government *nondefense* spending, again for the top 10 industries in 2002, in descending order. This list overlaps heavily with the list for federal nondefense spending, especially among the high-tech industries and durable goods industries. Quantitatively, it is obvious that nondefense spending accounts for a smaller share of industry sales than defense spending, significantly so for the top two or three industries. A natural effect of the smaller magnitude of industry supply to nondefense needs is that the ranking of sales for nondefense spending is slightly less stable across years than that for defense spending. Detailed differences notwithstanding, the high correlation between these two lists implies that an industry's total

[8] See Table 1a in Wang (2013) for the exact ranking of these industries in other select years.

sales to the federal government for all purposes should be a robust measure of its dependence on federal demand and, in turn, of its exposure to fiscal uncertainty.

To provide a summary view of the cross-industry distribution of the share of sales that ultimately go to meet the federal government's final demand, Figure 1a depicts the cross-sectional distribution of the share of each industry's total sales to the government between 1998 and 2011. We sum defense and nondefense sales because they are shown to be highly correlated in each industry. Two features emerge. First, the distribution of the sales share is rather skewed: federal demand accounts for less than 5 percent of sales in up to three quarters of the industries, but for over 20 percent of sales in just a handful of industries. This suggests that the importance of federal demand and, in turn, the sensitivity to policy uncertainty, may not differ meaningfully for a large fraction of the industries. Instead, we are likely to detect significant differences in the impact of policy uncertainty only by comparing the handful of industries with nontrivial reliance on federal demand with the remaining industries. Second, the share of ultimate industry sales to the federal government increased steadily over this period, especially between 2002 and 2010, but started to fall since 2010. This increase is somewhat skewed toward industries that are already highly ranked in terms of shares of sales to the federal government. The overall upward trend is consistent with the aggregate time-series of the share of federal government spending in GDP, and this is mostly driven by defense spending (Figure 1b).

We next report some simple comparisons of employment and hours growth across industries, sorted by their share of sales to the federal government.[9] Again, we sum defense and nondefense sales because of their high correlation, and we rank industries by this total share.[10] We use payroll data collected through the Current Employment Statistics survey (CES, also known as the payroll survey) and compiled by the Bureau of Labor Statistics (BLS). To be precise, we use data on total employees (referred to as "all employees" by the BLS), production and nonsupervisory employees, and average weekly hours of production employees for private nonfarm industries.[11] The time-series of average weekly hours of total employees is available only since 2005, too short a period to support an analysis. As elaborated in the next section, we compare the adjustment dynamics of employees versus average hours to enhance the identification of the impact of changing uncertainty, since theory suggests that the two margins of total

[9] In the rest of the paper, the share of direct plus indirect sales is simply referred to as the share, unless otherwise noted.

[10] We have ascertained that the patterns are indeed extremely similar if we instead sort by sales to defense or to nondefense spending separately.

[11] For brevity, we refer to production and nonsupervisory employees simply as production employees and to average weekly hours simply as average hours, unless additional precision is necessary.

labor input should react differently because of the difference in adjustment costs. The CES data by industry are organized by the North America Industry Classification System (NAICS) codes, which we match to the industry codes used in the BEA's annual IO tables. We use data at the level of three- and four-digit industries whenever available, in which case data for the corresponding two-digit industries are excluded.[12] The resulting 59 IO industries correspond to 80 NAICS codes.

Figure 2a shows the weighted-average growth rates for total employees from January 2008 to March 2013 for the industries in the top (solid green line) and the bottom (dashed red line) quartiles based on the average share of total sales to the federal government over the 2002-to-2007 period. The falloff in total employees was much steeper during the recession in those industries that sell more of their products to the government. They then recovered at a faster clip in 2010 and 2011. For comparison, Figure 2b depicts the comparison between the same two sets of industries over the longer sample period starting in 1990. It shows that the industries with high shares of total sales driven by government demand are more cyclical in general, with the differential especially wide during the 2001 recession and the Great Recession. This is consistent with the identity of the top 10 industries reported in Tables 1 and 2 in terms of their shares of sales going to the federal government: we would expect them to have been hit harder when the tech boom turned into a bust, and to be intrinsically more cyclical as well.

Figure 3 depicts the growth of production and nonsupervisory employment over the period since 1990; it is the counterpart to Figure 2b. It is clear that the general contour of growth is extremely similar for production employees and total employees, in both sets of industries. Two relatively noticeable differences are: 1) the growth in production employment is somewhat more volatile, implying that fluctuations in the total number of employees are largely accounted for by fluctuations in the number of production workers, and 2) for those industries ranked in the top quartile by the share of sales eventually accounted for by the federal government, the number of nonproduction employees, and in turn total employees, contracted more during the Great Recession than in the 2001 recession, while the number of production employees fell by about the same percentage during the two recessions. This seems consistent with the perception that firms became extremely risk averse during the Great Recession and "cut to the bone."

Figure 4 plots the counterpart to Figure 3 for average weekly hours of production workers since 1990; we use a six-month trailing average growth rate (at an annualized rate) because monthly growth

[12] Hence, only these two-digit industry data are used: 22, 23, 42, 44, 51, 61, and 81.

rates are too volatile. The dynamics of average hours are evidently different from those of employees. First, the growth in average hours is much less persistent. Second, the low-frequency movements are not as tightly correlated with the business cycle. More importantly, although average hours are somewhat more volatile for those industries in the top quartile than those in the bottom quartile in terms of the share of their output sold to the federal government, the disparity between them is at most weakly related to the business cycle. This suggests that the usual indicators of aggregate economic conditions, such as GDP or total employment, will have much lower explanatory power for movements in average hours. A further implication is that the estimated impact of uncertainty shocks on average hours is unlikely to be driven by cyclical factors.

To get a sense of the importance of these two sets of industries in terms of total employment, Figure 5 plots on the left axis the share of total employees on the payrolls of all private nonfarm industries accounted for by the industries in the top and the bottom quartiles, respectively, in terms of the share of each industry's sales to the federal government. It plots on the right axis the ratio of total employees in the top quartile to the bottom quartile of industries. It is clear, and not very surprising, that industries with high shares of sales to the government account for a much smaller fraction of total nonfarm private payroll, and that this fraction has been trending downward since 2000. Furthermore, this overall downward trend exhibits a cyclical pattern, falling during recessions and early recoveries, and rising moderately during booms.

According to Figures 2a and 3, over the first three quarters of last year, average payroll growth in industries with the highest shares of sales to the federal government slowed more than in industries with the lowest shares of sales to the government. The deceleration, however, seems to have reversed since last October. This suggests that concerns about a possible hard landing in China plus continued woes in Europe may have played as prominent a role as heightened uncertainty concerning domestic fiscal policy. For that matter, these industries similarly experienced a more pronounced slowing in payroll growth during the first half of 2011, when the uncertainty surrounding fiscal policy was probably also elevated, culminating in the debt-ceiling showdown in early August. On the other hand, the first half of 2011 also saw major disruptions from natural disasters, such as the earthquake and tsunami in Japan. Therefore, it is necessary to control for other influences on an industry's employment dynamics in order to isolate the effects of fiscal policy uncertainty more cleanly.

III. Review of Literature on the Effect of Uncertainty on Labor Adjustments

We now briefly review the theoretical foundation for the adjustment dynamics of employment versus average weekly hours, particularly how the dynamics may change in response to variations in uncertainty. We discuss along the way which theories may be particularly applicable to our industry-level dataset, including the likely effect of aggregation on the adjustment dynamics, and what the theories imply about the specification of the regressions to detect the direct effect of policy uncertainty on employment across industries. For a broader review of the stylized facts of uncertainty and the impact of fluctuations in uncertainty, see Bloom (2013).

In general, theoretical as well as empirical work, from Bernanke (1983) to Bloom (2009) for example, has shown that an unexpected increase in uncertainty induces firms to pause in adjusting their capital and the number of employees, and thus leads to a fall in activity in the aggregate. Between investment and employment, the effect of time-varying uncertainty is much greater on investment than on employment because the cost of adjusting capital is considerably greater than the cost of adjusting employees when both categories of costs are considered, as found in Bloom (2009). In contrast, since changing average hours does not incur meaningful adjustment costs, average hours in principle should not be affected directly by exogenous fluctuations in uncertainty. Thus, by examining both payroll employment and average hours, we should, in principle, be better able to identify the effect of uncertainty.

Labor input in production is measured using the (quality-adjusted) total number of hours worked, which is the product of the number of employees and the average number of hours worked during each unit of time. Hence, the total amount of labor input can be changed by adjusting either payroll employment or average hours; employment is often referred to as the extensive margin while average hours reflect the intensive margin of adjustment. Arguably the foremost distinction between payroll and average hours that is relevant for studying the impact of uncertainty concerns adjustment costs: it is generally agreed that hiring and firing are subject to adjustment costs—costs incurred only when a change is made— whereas altering the average number of hours is not. Note that this does not preclude a wage schedule that increases in the number of average hours, which is in fact commonly observed in practice, such as the overtime wage premium. Such increasing marginal cost is not an adjustment cost in that it depends on the level of the input regardless of whether there is a change.

In terms of the reaction to unexpected changes in uncertainty, the presence of employment adjustment costs means that firms are more reluctant to hire or fire workers when uncertainty is high than when uncertainty is low. The logic is that whatever changes the firms might make are more likely to prove to be suboptimal later if the second moment (volatility) of an economic variable's distribution is high, since the relevant economic factors (such as demand from the government) are expected to continue to fluctuate more, and the adjustment costs the firms would have paid would have been wasted. In fact, as a result they might have to incur additional adjustment cost in order to reverse the previous changes. Therefore, they would prefer to wait.

The strength of the real-options effect of uncertainty turns out to depend crucially on the specific functional form of the adjustment costs. In particular, Bloom (2009, p. 669) finds that the presence of some form of nonconvex adjustment costs (either a fixed cost or partial irreversibility) is needed for uncertainty to generate noticeable effects on investment, which is absent when convex adjustment costs alone are present. This is because the option value of doing nothing exists only with nonconvex cost, which jumps discretely at any departure from zero (change). Consequently, there exists an inaction zone, since only changes in capital and workers above a certain threshold are worth making, as the resulting benefit becomes sufficient to cover the discrete cost. Greater uncertainty widens the inaction zone, as firms delay investing and hiring (or firing) that they would otherwise have undertaken. Convex cost (such as represented by a quadratic function), in contrast, exhibits no such kink at zero, and thus generates no option value. It in fact favors small adjustments because of the increasing marginal cost. Bloom (2009) finds reasonably robust evidence for the presence of nonconvex costs of adjusting labor (hiring, training, and firing) at the firm level. A few earlier studies, such as Hamermesh and Pfann (1996), also document clear evidence of a fixed-cost component of hiring and firing in micro data, especially at the plant level.

In the context of this study, combining the above research findings yields the following argument for expecting cross-industry heterogeneity in the way policy uncertainty affects adjustments in industry employment. For any given degree of uncertainty concerning federal spending, the higher the fraction of a firm's output sold to the federal government, the more important the uncertainty is to the firm's overall sales, and in turn to the optimal adjustment of its payroll. All else being equal, the firm should be more cautious in adjusting its payroll in response to a given increase in uncertainty about federal fiscal policy. To be more precise, this argument can be illustrated using equations as follows. First, assume the following cost function for adjusting employment (analogous to the capital adjustment cost function in Abel and Eberly 1994), which contains a nonconvex component:

$$G(E_t, L_t) = \begin{cases} a^+ L_t + b^+ E_t + c^+ \left(\frac{E_t}{L_t}\right)^2 L_t & \text{if } E_t \geq 0, \\ a^- L_t + b^- E_t + c^- \left(\frac{E_t}{L_t}\right)^2 L_t & \text{if } E_t < 0. \end{cases}$$

E and *L* denote the gross number of employees adjusted and currently in the labor pool, respectively. A positive *E* corresponds to hiring, while a negative *E* to firing; with homogeneous labor and adjustment costs, a firm never does both simultaneously. aL_t is the fixed cost component, which depends not on the change but on the level of employment. In this formulation, we allow hiring and firing cost to be asymmetric, for which there is some evidence (to be discussed later), although the asymmetry has no impact on the qualitative conclusion of the dynamics of employee adjustment in response to increased uncertainty. The presence of a fixed-cost component gives rise to an inaction zone in terms of the (shadow) value of an employee, delineated by a hiring and a firing threshold, respectively. The firm hires only if the value of a new employee exceeds the hiring threshold, and it fires when the value of the employee falls below the firing threshold. Specifically, the rate of employment adjustment can be characterized as

$$\frac{E_t}{L_t} = \begin{cases} \frac{1}{c^+}\left(\lambda_t - b^+\right) & \text{if } \lambda_t \geq \overline{\lambda}_t\left(a^+, b^+, X_t\right), \\ 0 & \text{if } \lambda_t \subset \left[\underline{\lambda}_t\left(a^-, b^-, X_t\right), \overline{\lambda}_t\left(a^+, b^+, X_t\right)\right], \\ \frac{1}{c^-}\left(\lambda_t - b^-\right) & \text{if } \lambda_t < \underline{\lambda}_t\left(a^-, b^-, X_t\right). \end{cases} .$$

λ_t denotes the shadow value of an additional employee, $\overline{\lambda}_t(.)$ the hiring threshold and $\underline{\lambda}_t(.)$ the firing threshold. X_t denotes the set of variables relevant for the firm's decision (for example, productivity, wages, and sales). The inaction zone widens following an increase in uncertainty regarding demand and hence sales:

$$\frac{\partial \overline{\lambda}_t\left(a^+, b^+, X_t\right)}{\partial \sigma_Y^2} > 0 \text{ and } \frac{\partial \underline{\lambda}_t\left(a^-, b^-, X_t\right)}{\partial \sigma_Y^2} < 0.$$

σ_Y^2 denotes the variance—a measure of the uncertainty—of total demand *Y*. σ_Y^2 is a weighted average of the variance of sales to the government (σ_{YG}^2) and the rest of sales (σ_{YN}^2), plus their covariance. That is, $\sigma_Y^2 = s_G^2 \sigma_{YG}^2 + (1-s_G)^2 \sigma_{YN}^2 + 2 s_G (1-s_G) \sigma_{YG,YN}$, where s_G is the share of sales to the government, and $\sigma_{YG,YN}$

is the covariance between these two components. Therefore, assuming the variance of sales to the government is uncorrelated with the variance of sales to other customers, we have[13]

$$\frac{\partial \overline{\lambda}_t\left(a^+,b^+,X_t\right)}{\partial \sigma_{YG}^2} = s_G^2 \frac{\partial \overline{\lambda}_t\left(.\right)}{\partial \sigma_Y^2} \quad \text{and} \quad \frac{\partial \underline{\lambda}_t\left(a^-,b^-,X_t\right)}{\partial \sigma_{YG}^2} = s_G^2 \frac{\partial \underline{\lambda}_t\left(.\right)}{\partial \sigma_Y^2}.$$

These two comparative statistics results spell out our intuitive conclusion earlier: all else being equal, the higher the share of a firm's sales accounted for by federal government final demand, the wider the expansion of its inaction zone following an increase in the uncertainty about government demand. Hence, the firm becomes more cautious in adjusting its employees. In particular, its hiring or firing decision becomes less responsive to changes in demand or productivity. Note, however, that the implication for the net adjustment of employees can be ambiguous, depending on whether the firm is closer to the hiring or the firing thresholds.

Empirically, however, the magnitude of this differential impact on employee adjustment of uncertainty regarding government demand may be quite modest. Bloom (2009) finds that the costs of adjusting employees are substantially smaller than those associated with adjusting the capital stock. Besides, investment is a gross flow whereas changes in employees are almost always a net flow in observed data.[14] Thus, compared with changes in payroll, investment reacts much more strongly to uncertainty shocks. The implication for this study is that we expect to find only a moderate effect of variations in uncertainty on employment growth.

Furthermore, aggregation along multiple dimensions is almost certain to further damp the size of the impact of uncertainty shocks on net changes in employment. In general, the smaller the productive unit, the stronger the evidence for a fixed-cost component—manifest in lumpier adjustments—and hence the impact of uncertainty shocks. The observed dynamics of adjustment tend to be smoother the larger the number of units involved because of averaging. Thus, the effect of uncertainty shocks is moderated even at the level of firms, especially large firms, which comprise a large number of productive units (see Bloom 2009). Moreover, in reality, firms employ multiple types of labor (and capital), and aggregation across these heterogeneous types renders the observed adjustments of total employees at the individual firm level smoother than the benchmark case of a single type of workers.

[13] More generally, all that we need is for the variance of overall demand to rise with s_G for a given increase in the variance of government demand. This is satisfied so long as $\partial\sigma_{YN}^2 / \partial\sigma_{YG}^2 < s_G / \left(1 - s_G\right)$, that is, the variance of a firm's sales to non-government customers does not comove too closely with the variance of its sales to the government.

[14] Exactly for these reasons, the topic of the option value of waiting when faced with uncertainty has been more prominent in the literature on investment (see, for example, Dixit and Pindyck 1994) than in studies of employment.

We can infer that this smoothing effect due to averaging is most likely stronger at the industry level, which comprises many firms. On the other hand, the exact magnitude of the real-options effect at these more aggregated levels depends on not only the micro parameters, but also the distribution of micro units in terms of their distance from the hiring and firing thresholds. For instance, the real-options effect at the micro level should generally still show through at the industry level, or even the aggregate level, to the extent that there is a sufficient mass of firms bunched just below the hiring threshold or just above the firing threshold of the inaction zone. In general, Bloom's findings (2009) imply that more firms are clustered near the hiring cutoff than near the firing cutoff, especially for growing industries. Thus, the net effect of heightened uncertainty is a slowing in employment growth. In theory, it is possible that this net impact is reversed for shrinking industries—declines in employment in fact slow. In reality, however, other adverse effects of an increase in uncertainty, such as higher financing costs, may well more than offset the effect due to greater caution and still lead to a lower rate of employment growth.

In addition to measuring the number of total employees on the payroll, the BLS also reports the number of a sub-group of employees—production and nonsupervisory workers—separately.[15] These are employees who contribute directly to the production process, and thus have more immediate impact on near-term sales than the rest of employees (that is, nonproduction and supervisory workers). It is conceivable that the real-options effect is stronger for nonproduction employees than for production workers, since the former do not directly affect current production, and thus the net benefit from waiting to make adjustments is likely higher. At the same time, there seem to be few reasons to expect the precautionary motive on the part of nonproduction workers to be more sensitive to changes in uncertainty than that of production workers. If so, the growth of nonproduction employment, and in turn that of total employment, should in principle slow more than the growth of production workers when uncertainty rises. There exist, however, no previous studies that try to gauge whether such a difference exists, let alone its size. Moreover, even if it exists in principle, this differential may not be detectable in actual data because of measurement errors, such as misclassification of employees. Treating this as an empirical question, we examine the dynamics of production workers in addition to those of total employees and compare the relative magnitudes of the reactions to uncertainty.

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[15] How a worker in this group is referred to depends on the industry. According to the BLS, "production and related employees" refers to workers engaged in various aspects and stages of production operations in the manufacturing, mining, and logging industries, while "nonsupervisory employees" refers to those individuals in private, service-providing industries who are not above the working-supervisor level. For more details, see Chapter 2 (Employment, Hours, and Earnings from the Establishment Survey) of the BLS Handbook of Methods.

In contrast to payroll employment, average hours can be altered costlessly, and so firms should always adjust this intensive margin to its optimal level regardless of the degree of uncertainty. This optimal level of average hours, however, likely depends on the level of employment, and hence indirectly on the level of uncertainty. Specifically, when uncertainty rises, a firm that has planned on hiring more workers is likely to postpone hiring and consequently has fewer workers than it would likely otherwise prefer. Then, to meet production goals, it would increase the average number of hours of each worker. On the other hand, if a firm postpones laying off workers because of high uncertainty, then the average hours worked may be reduced as a result. On net, the former scenario is likely to dominate because of other costs that heightened uncertainty induces, such as more expensive funding. In sum, average hours are likely to rise, but can also fall with uncertainty, depending on the optimal response of employment to uncertainty. Therefore, regressions of average hours should control for the number of employees, and conditioned on this, average hours should not react to uncertainty shocks.

It should be noted that the option value of waiting discussed above applies to *gross* adjustments by firms of the number of workers (or gross flows as commonly referred to in the labor literature) because of the presence of gross hiring and firing costs. The same mechanism can also apply to net adjustments if there exist separate costs for *net* hiring or firing. Studies of employment flows at establishment and firm levels, such as the influencial work of Davis and Haltiwanger (1992), suggest that there may be both gross and net adjustment costs. But the former likely dominate the overall dynamics of employment because Davis and Haltiwanger (1992), among others, also document that the magnitude of gross flows far exceeds that of net flows, at least in terms of unconditional changes of payroll employees. This implies that, apart from all the reasons discussed above, the effect of greater uncertainty on net hiring (or firing) by firms is most likely smaller than the effect on gross hiring (and firing).

Perhaps more importantly, the observed change in employment also includes adjustments initiated by workers: it is a net flow equal to hiring net of total separations, which include not only layoffs but also quits and separations for other reasons. It is likely that the rate of separations initiated by workers also slows following an unexpected increase in uncertainty, because workers also become more cautious, and therefore less likely to quit. These two gross flows would then offset each other at least partially, leaving the net change in employment less sensitive than its gross components to uncertainty shocks. By comparison, adjustments by firms of average hours are almost certainly in only one direction, since firms should try to equalize the marginal cost across workers. All these suggest that the combined effect on empirical estimates is to diminish the chance of finding a significant difference between employment and average hours growth in terms of their reaction to uncertainty shocks.

In the context of our cross-industry analysis, the positive correlation between uncertainty and caution on the part of workers may attenuate the differential impact across industries of increased policy uncertainty on firms' adjustments of payrolls to the extent that workers employed by industries more reliant on federal demand also recognize the greater importance of policy uncertainty, and hence grow even more cautious than workers in other industries. Therefore, for us to find a differential impact of policy uncertainty on net payroll adjustment across industries, it is necessary that the cross-industry differential in workers' caution not fully offset that of firms.

In addition to the direct effect of inducing firms to postpone hiring or firing, heightened uncertainty can also reduce the sensitivity to demand shocks of firms' employment adjustments. That is, for a given unexpected rise in demand, firms increase the number of workers less when uncertainty is higher, and vice versa. In a regression of payroll growth on output growth and uncertainty (with other controls and demand instruments), this will show up as a negative coefficient on the interactive term between output growth and uncertainty. The logic of the more subdued reaction is the same as above: the greater the uncertainty, the more firms prefer to wait instead of altering inputs immediately to the level that would be optimal given the new information regarding demand. Bloom, Bond, and Van Reenan (2007) find supporting empirical evidence for this interactive effect using U.K. firm data. For the same reasons as discussed above for likely cross-industry differences in the direct real-options effect of uncertainty, we expect this dampening effect of uncertainty on the sensitivity of employment to output to differ across industries as well. Specifically, employment in industries that sell higher fractions of their output ultimately to the federal government likely becomes less sensitive to their own output growth when uncertainty regarding federal fiscal policy rises.

Previous studies have also noted another aspect of adjustment costs that is special to labor: the asymmetry between hiring and firing costs. Typically firing cost exceeds hiring cost. This is primarily the result of labor market regulations that place various restrictions on firms against shedding labor, restrictions that are most prominent in the developed economies of Europe (see the survey in Hamermesh and Pfann 1996). To the extent that the fixed component of firing cost exceeds that of hiring cost, the inaction threshold for firing should be wider than that for hiring, all else being equal.[16] Hence, it is possible that firms would hesitate to fire more than they would hesitate to hire when faced with a higher degree of uncertainty if the resulting *increment* (widening) of the firing threshold were greater than the increment of the hiring threshold. So the asymmetry in labor adjustment costs has the potential to

[16] This is conditional on the workers having been hired already. Unconditionally, the expectation of high firing cost in the future should render firms more cautious about hiring as well.

produce seemingly counterintuitive reactions to changes in uncertainty. At least it leads to less definite predictions about the impact of uncertainty on net payroll adjustment. This is probably not a major concern for this study, since the much more flexible labor market in the United States means that firing cost is likely to exceed hiring cost only modestly, if at all.

The difference between employment and average hours in terms of adjustment costs also has implications for how they respond to changes in the level (the first moment) of the relevant economic factors. Adjustments along the extensive margin tend to be utilized when the change needed is expected to be relatively persistent, for example because the fluctuation in sales is expected to last a while. By the same logic, adjustments along the intensive margin tend to be made when the change is expected to be temporary.[17] So, if the expected persistence of changes in the first moment of the relevant economic variables, such as government demand, is not adequately accounted for, it can potentially bias the estimated effect of uncertainty on employment. For example, if a high level of uncertainty regarding government demand is accompanied by the expectation of a long-lasting decline in that demand, then the negative impact of uncertainty on employment may be overestimated if the persistence of the demand reduction cannot be fully controlled for because forecasts are available only for a limited horizon. On the other hand, if the decline in demand is expected to be short-lived, then the effect of uncertainty may be underestimated.

There are probably other reasons, mostly owing to data limitations or measurement errors, that can obscure the different behavior of growth in payroll versus growth in average hours at different levels of uncertainty that would normally exist because of their difference in terms of adjustment costs. In particular, employment as reported in the CES survey by the BLS is defined as "persons on establishment payrolls who received pay for any part of the pay period that includes the 12th day of the month." It does not distinguish between full-time and part-time workers. At the same time, average weekly hours "are the total weekly hours divided by the employees paid for those hours." This means that a change in average hours can stem from a change in the mix of full- versus part-time workers, even if each individual works the same number of hours. This suggests that the measured changes in employment and average hours in the dataset are more closely linked than is recognized in theoretical models, and this can bias in either direction the true difference in their respective reaction to uncertainty.

[17] For example, Ramey and Vine (2006) show that the auto industry has increased its use of overtime and inventory-adjustment shutdowns since 1984 relative to changing the number of shifts or line speeds, both of which entail altering the number of workers, and much of this behavioral change can be attributed to the decrease in the persistence of sales since 1984.

In summary, we expect increases in uncertainty, including uncertainty about federal fiscal policy, to exert a moderately negative impact on employment growth after we control for effects of the other relevant factors, primarily past and expected future changes in demand and the persistence of employment adjustments. We also expect this deleterious effect to be more pronounced for industries that sell non-negligible shares of their output directly and indirectly to the federal government. In principle, the impact of policy uncertainty changes should be noticeably larger on payroll growth than on increases in average hours, and the latter may even respond in the opposite direction. However, the above discussion also makes clear that there are a number of reasons, often related to data limitations, why in practice the effect of policy uncertainty on employment versus average hours growth may not be significantly, or even discernibly, different. Therefore, it becomes more an empirical question.

IV. Panel Regression Specifications

This section discusses how to specify panel regressions that are consistent with the applicable theories reviewed above. The main challenge is to control adequately for the factors, other than policy uncertainty, that are also relevant for an industry's employment growth in order to uncover the marginal effect of policy uncertainty. Among these other factors, a primary one is past and expected future growth of demand, especially from the federal government. For instance, those industries that sell more to the government may have grown faster in the early days of the recovery because they were helped by increased orders from the government financed under the stimulus package, and their employment growth may have slowed more since the second half of last year because federal spending has waned following the expiration of the stimulus. Hence, adequate controls for demand for an industry's products, especially for its expected future growth, are crucial to minimize the likelihood of biasing the estimated marginal effect of policy uncertainty.

1. Regressions for All Private Nonfarm Industries

First, we present the regression specifications for the comprehensive panel that includes all the private nonfarm industries whose payroll employment and average weekly hours are reported in the CES dataset. The advantage of this sample—its breath of coverage—also places a serious limitation on specifications: industry output is not available and thus cannot be explicitly controlled for in the regressions. Therefore, for the two measures of employment available in this dataset (total employees and production employees), we run the following fixed-effects panel regression, using quarterly industry-level data.

$$\begin{aligned} n_{it} &= \alpha_i + \beta_0 PUI_t + \beta_1\left(s_{it}^{G1} PUI_t\right) + \sum\nolimits_{j=1}^{\tau} \rho_j n_{i,t-j} + \sum\nolimits_{k=D}^{ND} \delta_{sk}\left(s_{it}^{k} g_{t+4|t}^{k}\right) + \sum\nolimits_{k=D}^{ND} \delta_k g_{t+4|t}^{k} + \delta_s s_{it}^{G} \\ &+ \sum\nolimits_{j=0}^{q}\left[\gamma_{sEg,j}\left(s_{it}^{Exp} g_{Exp,t-j}\right) + \gamma_{Eg,j} g_{Exp,t-j} + \gamma_{sE,j} s_{it}^{Exp}\right] \\ &+ \sum\nolimits_{j=0}^{p}\left[\gamma_{sDg,j}\left(s_{it}^{D} g_{D,t-j}\right) + \gamma_{Dg,j} g_{D,t-j}\right] + \theta X_{it} + \varepsilon_{it}. \end{aligned} \tag{1}$$

The dependent variable, n_{it}, represents growth in the number of total or production employees for industry i in quarter t, calculated as the log difference for the last month of each quarter relative to three months ago (which is equivalent to the average monthly growth rate within the quarter). Its own lags (up to τ lags) on the right-hand side are meant to capture the partial adjustment dynamics of employment.[18] The presence of these lags leads to a dynamic panel. Since the time-series (T) dimension of our data is sufficiently large, about the same as the cross-section (N) dimension in fact, the within-groups (WG) estimator is consistent, as shown in Alvarez and Arellano (2003), among others.[19] Moreover, the WG estimator should produce no larger asymptotic bias than the GMM estimator (developed in Arellano and Bond, 1991, among others), as Alvarez and Arellano (2003) also show that the former is of order 1/T while the latter is of order 1/N.[20]

There is, however, a different reason for possibly inconsistent WG estimates in our large-N and large-T dynamic panel: this can occur if the slope coefficients differ across industries. Unlike the additive heterogeneity represented by the industry fixed effect (α_i), random slope coefficients in a dynamic panel render the WG estimator inconsistent.[21] In contrast, the mean-group (MG) estimator developed in Pesaran and Smith (1995) is consistent for such heterogeneous dynamic panels. The MG estimator regresses the individual time-series separately and then averages (with equal or relative-variance-based weights) the parameter estimates in the cross section. It is therefore not robust to cross-sectional dependence, which is almost certainly present in our industry data and thus can render inferences invalid. Instead, as we will discuss further below, the CCE estimators developed in Pesaran (2006) can

[18] We also experimented with a specification without lags of employment. It does not alter the results qualitatively, other than yielding somewhat more negative coefficients on the variable measuring policy uncertainty.
[19] Two major earlier studies showing that the WG estimator is consistent as time dimension T → ∞ are Anderson and Hsiao (1981) and Nickell (1981). The within estimator can, in fact, be superior to the two-stage least squares instrumental variable estimator if the instruments are weak.
[20] The GMM estimator remains consistent while the WG estimator does not for dynamic panels with a large N but a small T dimension, such as typical in firm- or establishment-level datasets.
[21] Wooldridge (2005), among others, shows that, with suitably transformed data, the standard WG estimator can yield consistent estimates of the average slope coefficients (called the average partial effect) in a static panel if the individual-specific slope is correlated with the long-run mean or trend of the regressors but not their deviations.

account for general cross-section dependence in heterogeneous panels. According to Monte Carlo simulations conducted therein, the CCE estimators compare favorably with the basic MG estimator, including in samples of small to moderate sizes (with N and T in the range of 30 to 50). We will apply the CCE estimators in our analysis to account for possible slope heterogeneity along with unknown general cross-industry dependence.

The *PUI* is the composite index of policy uncertainty constructed by Baker, Bloom, and Davis (2013).[22] It is a weighted average of subindexes that measure four aspects of economic policy uncertainty: (i) the frequency of references to economic and policy uncertainty in 10 leading newspapers (keywords chosen for the news searches cover not only fiscal policy,which includes spending, subsidies, and taxes, but also monetary policy); (ii) dollar-weighted numbers of federal tax code provisions set to expire in future years; (iii) the degree of disagreement among professional forecasters over future federal, and state plus local government purchases; and (iv) disagreement among the same set of forecasters over the consumer price index (CPI) inflation.[23] In the final composite index, component (i) is assigned a weight of one-half, while each of the other three series a weight of one-sixth. In our baseline specification, we include only the contemporaneous level of the *PUI*. This is adapted from the specification in Bloom, Bond, and Van Reenen (2007) that includes both the level and the change in uncertainty in the current period.[24] We omit the contemporaneous change in the *PUI* because it is insignificant in virtually all specifications. Instead, we experiment with alternatives that include lagged levels of the *PUI*, to explore whether there are delays in the response of employment to changes in uncertainty.

s_{it}^{G1} is a binary dummy variable defined based on s_{it}^{G}, the share of an industry's total sales to the government in its output, where s_{it}^{G} equals the sum of defense and nondefense spending shares ($s_{it}^{G} = s_{it}^{D} + s_{it}^{ND}$). s_{it}^{G1} equals one for industries with shares of sales to the government above a certain threshold, and zero otherwise. This formulation captures the idea that policy uncertainty shocks are likely to have meaningfully different impacts only on industries with a nontrivial share of sales to the government. We explore where the threshold lies. β_0 measures the general, uniform-across-industries, marginal effect of a higher level of policy uncertainty, while β_1 captures any differential impact of policy uncertainty on the industries that depend most heavily on government purchases.

[22] The original data are monthly, downloaded from http://www.policyuncertainty.com/us_monthly.html.
[23] For more details, see Baker, Bloom, and Davis (2013), http://www.policyuncertainty.com/methodology.html.
[24] Bloom et al. (2007) include both the current level and the change in policy uncertainty to tease apart how much of the effect of uncertainty is due to a high level and how much is due to an increase.

Ideally, one would want to control for an industry's demand conditions in explaining its labor input. However, own output data for most of these industries are available only annually. As a noisy proxy, we consider two alternative sets of aggregate variables to control for economic conditions. The first set is based on current and lagged growth rates of federal defense spending ($g_{D,t-j}$) and exports ($g_{Exp,t-j}$), with up to p and q lags, respectively. They are weighted by s_{it}^{D} and s_{it}^{Exp}, each industry's share of output accounted for by federal defense spending and exports, respectively, to approximate the exogenous demand condition faced by each industry.[25] For completeness, the two growth rate series and the export share in output also enter separately. The share of defense spending is not included because it is highly correlated with the share of total federal government spending at the industry level, and the latter will enter as a regressor.[26] The lag terms are meant to capture the dynamic response of employment to changes in demand. In particular, compared with just the contemporaneous value, a number of lags may better capture the degree of persistence in spending of a defense program, which is in principle more relevant for firms' hiring decisions, as discussed in the previous section.

As discussed above, industry-specific, weighted, defense spending serves as a control for exogenous demand for an industry's products, which is less likely than aggregate output to be influenced by uncertainty. The weights also partially account for the greater cyclicality of those industries selling more to the government. Including weighted exports as another control for demand follows the same logic. Exports, especially in the short run, are much more influenced by foreign demand than by the exchange rate, which is also affected by domestic (monetary) policy and economic conditions. Exports are, of course, affected by the global component of demand fluctuations. These arguments of exogeneity in principle, however, do not rule out the possibility that, for a specific sample, defense spending and exports may be highly correlated with aggregate output empirically. This is, in fact, the case for our sample period since 1998. Defense spending has become moderately countercyclical, in contrast with its acyclical behavior in earlier periods, while exports are highly procyclical (Figure 6).[27] This means that statistically the coefficient on policy uncertainty will likely diminish in magnitude and significance when exports and defense spending are included.

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[25] The share of an industry's output sold directly and indirectly to satisfy exports is also calculated using the input-output tables, analogous to treatment of the share of sales to the government.

[26] When both shares are included, their coefficients have opposite signs and essentially the same magnitude.

[27] Stock and Watson (1999) find that defense spending is basically acyclical, using post-WWII data until 1997. Exports have become more procyclical in recent decades. For instance, the correlation between four-quarter real GDP growth and export growth is 0.62 since 1998, but only 0.27 for the post-WWII period as a whole.

In addition to federal defense spending that has already occurred, we also control for expected future growth of federal government defense and nondefense spending, denoted $g^{D}_{t+4|t}$ and $g^{ND}_{t+4|t}$, respectively, using the same-period forecasts from Global Insight (GI). Specifically, we use the forecasts made in quarter t of the cumulative growth of federal government defense and nondefense spending over the next four quarters (that is, until quarter t+4).[28] This four-quarter growth rate should be a better measure of the persistence of the change in government demand than forecast growth over shorter horizons. As discussed above, expectations of not only the growth rate itself but also the persistence of demand matter for firms' optimal choice of adjusting employment (through hiring or firing) versus hours.

To account for the cross-industry variation in the importance of federal government purchases, we also interact the GI forecasts with s^{D}_{it} and s^{ND}_{it}, each industry's share of output eventually sold to the federal government to satisfy defense and nondefense demand, respectively. We therefore also include the sum of the two shares, s^{G}_{it}, as a regressor; the two shares are too highly correlated at the industry level to enter separately. These controls should guard against the possibility of finding a significant coefficient on policy uncertainty due to periods of elevated uncertainty coinciding with periods of low expectations about the future growth of federal government spending. Simple unconditional correlation suggests that this may indeed be the case within our sample period—1998:Q1 to 2013:Q1—as evidenced by the negative correlation coefficients between the *PUI* and $g^{D}_{t+4|t}$, as well as between the *PUI* and $g^{ND}_{t+4|t}$, reported in Table 3.

An alternative set of "demand" controls is composed of contemporaneous and lagged growth rates of aggregate output, here GDP. Note that, unlike the first set of controls included in equation (1), GDP growth here already incorporates whatever adverse influence is exerted by policy uncertainty on aggregate activity, and so its inclusion may well bias downward the estimate of the coefficients on policy uncertainty. Specifically, the regression equation becomes:

$$\begin{aligned} n_{it} = {} & \alpha_i + \beta_0 PUI_t + \beta_1 \left(s^{G1}_{it} PUI_t\right) + \sum\nolimits_{j=1}^{\tau} \rho_j n_{i,t-j} + \sum\nolimits_{k=D}^{ND} \delta_{sk} \left(s^{k}_{it} g^{k}_{t+4|t}\right) + \sum\nolimits_{k=D}^{ND} \delta_k g^{k}_{t+4|t} + \delta_s s^{G}_{it} \\ & + \sum\nolimits_{j=0}^{q} \left[\gamma_{DY,j} \left(y_{t-j} Dur\right) + \gamma_{Y,j} y_{t-j}\right] + \theta X_{it} + \varepsilon_{it}. \end{aligned} \qquad (1')$$

[28] For comparison, we also examined the median forecast from the Survey Professional Forecasters (SPF), which unfortunately covers only total federal spending, but not defense and nondefense spending separately. The SPF forecasts have fairly similar time-series patterns to the GI forecasts, but are generally less volatile, being the median of individual forecasts.

In this equation, y_{t-j}, j = 0, … q, denote the growth rates of current and lagged GDP. *Dur* is a dummy variable that equals one for durable goods industries and zero otherwise. Including the contemporaneous value of this aggregate control is again meant to be conservative with regard to the coefficient on policy uncertainty because these should already embed the entire general influence of policy uncertainty on current activity. In addition, we also want to control for the greater cyclical variation in output, and hence employment, in those industries with high shares of sales to the government, which tend to produce durable (including high-tech) goods (as shown above). This is to minimize potential bias in the coefficient on uncertainty, since it also exhibits a cyclical component. To this end, we interact GDP growth with *Dur*, the durable industry dummy, to account for the greater cyclicality of those industries selling more to the government or to foreigners. Last, we also include the GI same-period forecast of four-quarter cumulative GDP growth on the right-hand side, plus its interaction with *Dur* to account for the durable industries' greater cyclicality.[29] These terms are summarized in X_{it}.

The final specification for growth rates of the total number of employees at the industry level uses growth of total employment in all private nonfarm industries as controls, which is the total-employee-weighted average of growth at the industry level. This specification follows from the CCE-type estimators derived in Pesaran (2006). Pesaran (2007) then applies the CCE estimators to test for unit roots in dynamic heterogeneous panels. The basic idea of the CCE estimators is to filter the individual-specific regressors using cross-sectional averages so that the effects of unobserved common factors, which can differ across individuals, are eliminated asymptotically (as N tends to infinity). Arbitrary correlations are allowed among both observed and unobserved common factors, which are otherwise assumed to be exogenous. In our analysis, the *PUI* can be regarded as an observed common factor. It is allowed to be correlated with any number of unobserved common factors in a general, albeit unknown, way. The coefficient on the *PUI* may be imprecise if it is too highly correlated with some unobserved common factors, but this seems unlikely given the VAR results in Bloom (2009) and Baker et al. (2013). This accords with the moderate size of standard errors surrounding the coefficient on the *PUI* reported in the next section.

The CCE estimators' empirical advantage is that they can be derived by augmenting the observed regressors with cross-sectional averages of the dependent variable and the individual-specific regressors. These controls can be used in the context of the WG pooled estimator or the original MG estimator (CCEP or CCEMG, respectively). According to Monte Carlo simulations in Pesaran (2006), the CCEP estimator of

[29] GI forecasts of total payroll are available only for all industries, not for private industries separately.

the coefficients on individual-specific regressors compares favorably with the CCEMG estimator, which in turn excels over the basic MG estimator, including in samples of small to moderate sizes (30 to 50 units and 30 time periods). One potential drawback of the CCE estimators in the context of our analysis is that the coefficient on the *PUI*-interaction term may be rather imprecisely estimated, since it is a near-linear function of a single observed common factor (the *PUI*) that is itself included in the regression. The moderate standard errors (to be reported later) of this coefficient suggest that this is a minor concern. In sum, we will mostly apply the CCEP estimator in this study, that is including the (weighted) cross-sectional averages as controls in the WG pooled regressions, but we will also use the CCEMG estimator for robustness checks.

In our context, the current-period growth rate of total employment of all private nonfarm industries serves as the cross-sectional average of the dependent variable, while lagged growth rates of this aggregate employment measure correspond to cross-sectional averages of the individual-specific regressors. All other variables already have their cross-sectional averages included, which are the aggregate variables themselves. To be exact, we specify the CCEP estimator as follows:

$$\begin{aligned} n_{it} &= \alpha_i + \beta_0 PUI_t + \beta_1 \left(s_{it}^{G1} PUI_t \right) + \sum\nolimits_{j=1}^{\tau} \rho_j n_{i,t-j} + \sum\nolimits_{k=D}^{ND} \delta_{sk} \left(s_{it}^{k} g_{t+4|t}^{k} \right) + \sum\nolimits_{k=D}^{ND} \delta_k g_{t+4|t}^{k} + \delta_s s_{it}^{G} \\ &\quad + \sum\nolimits_{j=0}^{q} \left[\gamma_{DN,j} \left(n_{t-j} Dur \right) + \gamma_{N,j} n_{t-j} \right] + \varepsilon_{it}. \end{aligned} \tag{1-CCE}$$

In this equation, n_{t-j}, j = 0, … q, denotes the current and lagged growth rates of the total number of employees in private nonfarm industries. We also interact them with *Dur*, the durable-goods dummy variable, to account for the greater cyclicality of these industries, as explained above. Within the framework of the CCE estimators, this additional set of control variables is warranted because n_{t-j} is a weighted cross-sectional average of the dependent variable, and it underweights the more volatile durable goods industries relative to an equal-weighted average. Adding extra controls for durable goods industries separately accounts for this difference and at the same time enables interpretation of both sets of control variables. It also offers the additional benefit of facilitating comparison with earlier specifications. All the other variables are defined in the same way as in (1').[30] Note that the forecast of the cumulative growth in federal government spending over the next four quarters, along with its interaction with the share of spending in industry output, is still controlled for in both specifications (1') and (1-CCE).

[30] GI forecasts of total payroll are excluded because they are available only for all industries, not for private industries separately.

The specifications for regressions (in growth rates) of average weekly hours of production employees are nearly identical to those for employment above, with just one additional control variable—the growth in the number of production employees. As discussed in the previous section, average hours do not react to changing uncertainty only, if conditioned on the number of employees. In growth rates, this suggests controlling for current and lagged growth in the number of employees. Moreover, the first-order condition for average hours points out that it should also depend on the wage rate. Note, however, that the theoretically correct concept corresponds to the allocative shadow wage, which can differ considerably from the observed wage due to various frictions. Empirical results confirm that observed wage rates exhibit little explanatory power, likely because they are too sticky. Consequently, we omit the wage from the regression specification.

In sum, to illustrate using the specification in (1') above, the corresponding regression for average hours is as follows:

$$\begin{aligned} h_{it} = \alpha_i + \beta_0 PUI_t + \beta_1 \left(s_{it}^{G1} PUI_t\right) + \sum\nolimits_{j=1}^{\tau'} \rho_j h_{i,t-j} + \sum\nolimits_{k=D}^{ND} \delta_{sk} \left(s_{it}^{k} g_{t+4|t}^{k}\right) + \sum\nolimits_{k=D}^{ND} \delta_k g_{t+4|t}^{k} + \delta_s s_{it}^{G} \\ + \sum\nolimits_{j=0}^{q'} \left[\gamma_{DY,j} \left(y_{t-j} Dur\right) + \gamma_{Y,j} y_{t-j} \right] + \sum\nolimits_{k=1}^{m} \phi_k n_{i,t-k} + \theta X_{it} + \varepsilon_{it}^{h}. \end{aligned} \tag{2}$$

Here h_{it} measures the growth rate of average weekly hours of production employees for industry i in quarter t, also calculated as the average monthly growth rate within the quarter. Among the explanatory variables, only two terms differ from those in (1') above: the own lags of h_{it}, and the contemporaneous and lagged growth in the number of production workers, $n_{i,t-k}$, $k = 1, \ldots, m$.

2. Regressions Controlling for Industry Own Output—Industrial Production Sector Only

As discussed above, the preferred specification for explaining employment growth is to control directly for, among other factors, movements in industry-specific demand that are unrelated to policy uncertainty. We use industry sales (shipments for goods industries) to proxy for industry-specific demand. Note that this tends to result in underestimates of the overall effect of policy uncertainty, which most likely depresses demand and hence sales, especially in those industries that produce investment goods. We can view these estimates as more conservative and thus closer to the lower bound of the true estimate. Industry sales are reported only at an annual frequency for most industries. The exception is the set of industries covered by the industrial production (IP) statistics collected by the Federal Reserve. Broadly speaking, the IP data cover primarily manufacturing, plus the mining and utilities sectors. The detailed industry classification maps to the level of classification used by the BEA for its IO tables, some of which are combinations of the NAICS industries (see Table A.1 in the appendix). The IP dataset reports shipments or (gross) output of those covered industries at a monthly frequency.[31]

Specifically, we estimate the following panel regression for employee growth in IP industries:

$$\begin{aligned} n_{it} &= \alpha_i + \beta_0 PUI_t + \beta_1 \left(s_{it}^{G1} PUI_t \right) + \beta_2 \left(y_{it} PUI_t \right) + \beta_3 \left[y_{it} \left(s_{it}^{G1} PUI_t \right) \right] + \sum\nolimits_{j=0}^{p} \gamma_j y_{i,t-j} \\ &+ \varphi \left(\ln Y_{i,t-1} - \ln N_{i,t-1} \right) + \sum\nolimits_{k=D}^{ND} \delta_{sk} \left(s_{it}^{k} g_{t+4|t}^{k} \right) + \sum\nolimits_{k=D}^{ND} \delta_k g_{t+4|t}^{k} + \delta_s s_{it}^{G} + \varepsilon_{it}. \end{aligned} \tag{3}$$

n_{it} here is defined in the same way as in (1) and (1'), the average growth rate in the number of total or production employees for industry i in quarter t. y_{it} is the analogously defined growth rate of industry i's output.[32] Interacting y_{it} with the two original terms related to the PUI leads to the two additional explanatory variables intended to gauge the degree to which greater policy uncertainty reduces the response rate of employment to a given (percentage) change in output. According to Bloom et al. (2007), an increase in uncertainty renders firms' optimal choice of payroll employment less responsive to a given change in output.

Contemporaneous and lagged output growth control for both current industry-specific demand and, at least partially, its persistence. As discussed in the previous section, the more persistent the demand, the more likely firms are to adjust labor input using the extensive margin—the number of employees—instead of average hours. The terms based on forecasts of government defense and nondefense spending growth help to control for industry-specific expected demand. $\ln Y_{i,t-1}$ and $\ln N_{i,t-1}$ are logarithms of industry i's output and employment in the previous period. The term $\left(\ln Y_{i,t-1} - \ln N_{i,t-1} \right)$ captures the partial adjustment (error-correction) dynamic of employment: conditional on productivity, output and the number of employees should be cointegrated, since average hours cannot have a permanent trend. Hence, any gap (in percentage terms) that opened up between the actual and the frictionless optimal number of employees, proxied by last period's output, should be partially closed in the subsequent period. All the other terms are as defined in the earlier equations.

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[31] The output reported corresponds to the so-called gross output instead of to value added, as defined in production theory, because the underlying data are mostly based on shipments. Gross output measures the real value of sales, while value added equals gross output net of purchased inputs. Gross output is likely more relevant than value added for firms' optimal choice of the number of employees because it is a more accurate measure of demand.

[32] Note that the coefficient on y_{it} is likely biased because of the simultaneity problem—inputs and output both respond positively to productivity—as first recognized by Marschak and Andrews (1944). To the extent that growth of productivity is not too serially correlated, lagged output growth can serve as instruments for current growth. More importantly, to the extent that productivity shocks are not correlated with policy uncertainty shocks, the ordinary-least-squares estimate of coefficients on PUI-related terms should be less susceptible to bias.

The regression for average weekly hours of production workers is specified analogously:

$$
\begin{aligned}
h_{it} = {} & \alpha_i + \beta_0 PUI_t + \beta_1 \left(s_{it}^{G1} PUI_t\right) + \beta_2 \left(y_{it} PUI_t\right) + \beta_3 \left[y_{it}\left(s_{it}^{G1} PUI_t\right)\right] + \sum\nolimits_{j=0}^{p} \gamma_j y_{i,t-j} \\
& + \sum\nolimits_{k=D}^{ND} \delta_{sk} \left(s_{it}^{k} g_{t+4|t}^{k}\right) + \sum\nolimits_{k=D}^{ND} \delta_k g_{t+4|t}^{k} + \delta_s s_{it}^{G} + \sum\nolimits_{k=1}^{m} \phi_k n_{i,t-k} + \varepsilon_{it}^{h}.
\end{aligned} \tag{4}
$$

The term $\left(\ln Y_{i,t-1} - \ln N_{i,t-1}\right)$, which was meant to capture the partial adjustment of employment, is removed. At the same time, the contemporaneous and lagged growth of production employees is added for the reason explained above.

V. Panel Regression Results

1. Regressions of the Total Number of Employees

We first report estimates of the impact of changing uncertainty on the growth of total employment, which we measure by the number of employees produced by the different specifications described above. As discussed in the previous section, total employment is likely the margin of labor input for which the real-options effect is most pronounced, since it includes nonproduction employees in addition to production workers. Table 4 reports the coefficient estimates from the panel regressions. The sample period spans 1998:Q1 to 2013:Q1. (See Table B.1 in the Appendix for summary statistics of all but the dummy variables used in the regressions.) The first year of the sample is chosen to coincide with the start of the annual input-output tables provided by the BEA. The regressions use industry employee data reported at the NAICS level.[33] All growth rates are annualized rates of growth over three months ago (which are equivalent to quarterly averages of monthly growth). The quarterly frequency is used because monthly fluctuations in employment contain much pure noise that is averaged out over a quarter, while the frerquency of quarterly data are still sufficiently high. We measure the share of an industry’s sales ultimately attributed to exports and government purchases, using the one-year lagged value to balance

[33] These regressions leave out three industries, NAICS 3364 to 3366, which constitute the "Other transportation equipment" industry in the IO tables. Collectively, they far exceed all other industries in terms of the share of sales to the government, so we exclude them to avoid the possibility of distorting the parameter estimates. Nevertheless, including them does not alter the significance of the coefficient on policy uncertainty, although its magnitude is slightly diminished.

the need for an up-to-date share and the minimal impact of contemporaneous growth on the share.[34] All regressions contain industry fixed effects, and the standard errors are clustered at the industry level. For brevity of presentation, we omit the coefficients on all industry dummy variables and also report only the sum of lagged coefficients on each industry's own total-employees growth.

The first column of Table 4 reports estimates from a regression that includes as controls only three lags of each industry's own total employment growth, the federal government purchase share, plus two recession dummies, and the post-2009 recovery dummy variables (so the omitted base period is the "normal" period between the 2001 and 2008–2009 recessions). The sum of the lagged coefficients on own growth does not change significantly if the lag length is expanded up to eight lags, with six lags maximizing the adjusted R^2. Here, we report the results with only three lags to be consistent with the later regressions with additional controls. The recession and recovery dummies all have the expected signs and are significant, whereas the coefficient on the federal spending share is insignificant.

The coefficient on the current-period policy uncertainty index (*PUI*) is negative and statistically significant, as shown in the first column of Table 4, meaning that a high level of policy uncertainty has a uniformly negative impact on industry total employment growth. A one-standard-deviation increase in policy uncertainty, which is 0.37 for the period since the beginning of our estimation sample in 1998, would reduce total employment growth across all industries by 0.80 (that is, 0.37 times 2.16) percentage point per year.[35] To put this in perspective, the annualized rate of quarterly growth of total employment on the payrolls of all private nonfarm industries has averaged 0.53 percent with a standard deviation of 2.38 percent over the same period, as shown in the appendix, in Table B5. More importantly, the coefficient on the interaction term between the *PUI* and the dummy variable identifying industries in the top quartile in terms of overall share of sales to the federal government is also negative and significant. Specifically, industries relying the most on government purchases curtail their overall employment growth by an extra 0.35 percentage point, on average, compared with the other industries when policy uncertainty is one standard deviation higher.

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[34] The current-year value is used for 1998. The shares calculated directly from the input-output tables remain fixed within each year. We also experimented with interpolating the shares within a year, based on the assumption that they evolve linearly from quarter to quarter. This makes little difference for the estimation results, with slightly smaller point estimates on the *PUI*-related terms, but virtually the same significance, because the shares evolve slowly from year to year.

[35] Note that we scale down the *PUI* by a factor of 100 to optimize the magnitude of the related coefficients for display in the result tables.

Columns (2) through (4) of Table 4 report the estimates when additional controls for either demand or general economic conditions are included. Column (2) adds two sets of industry demand variables: the current and two lags of export growth, along with their interaction with the share of each industry's output driven by exports; and the current and four lags of defense spending growth, along with their interaction with the share of an industry's sales eventually attributed to government purchases.[36] Adding a few more lags for either or both tends to raise the adjusted R^2 slightly, although it makes little difference for coefficients on the *PUI*-related terms. The sums of coefficients on the share-interacted growth rates of lagged export and defense spending are both positive and significant, whereas the growth rate of either demand series itself is insignificant. This suggests that the interaction terms are much better proxies for the demand condition at the industry level. The coefficient on the share of exports in output is positive, indicating that an industry's growth rate tends to rise when it exports more. Moreover, these controls take away some of the explanatory power of each industry's own lagged total employment growth, so the sum of the latter's coefficients is now somewhat lower. These demand controls also generally reduce the magnitude of the recession dummy variables.[37] This is consistent with the observation that both defense spending and exports are correlated with the business cycle over our sample period.

Interestingly, the coefficients on the GI forecasts of federal government defense and nondefense spending over the next four quarters (interacted with each industry's share of output eventually driven by federal government defense and nondefense demand, respectively) are negative, but only the coefficient on the interacted defense spending term is significant. This may seem puzzling at first glance, but there is an intuitive explanation. The forecast of total federal government defense spending, like the actual spending (illustrated in Figure 6), is countercyclical over our sample period. This is evidenced by its negative coefficient of unconditional correlation with past GDP growth as well as with total employment growth, at both the aggregate and the industry levels, as shown in Table 3. Moreover, for our sample period, the growth of defense spending happened to be high during periods when employment was weaker than can be accounted for (linearly) by output growth, as evidenced by its significant negative coefficient in a regression of total private payroll growth on lagged and forecast four-quarter GDP growth, along with forecasts of four-quarter growth in defense and nondefense spending,

[36] Coefficients on zero to three lags of defense spending growth are all small and insignificant. This seems consistent with the intuition that hiring responds more to persistent changes in government spending than to single-period changes.

[37] One exception is the more negative coefficient on the 2008-2009 recession dummy variable in column (2). This is consistent with the greater contribution to growth from exports and defense spending in this last recession.

shown in Table 5. This is largely because the timing of the Iraq war coincided with the anemic early recovery after the 2001 recession. At the same time, those industries selling a high share of their output to the federal government were hit hard by the 2001 recession and the high-tech slump. Hence, part of the "excess" cyclical movements in these industries' total employment growth loads up negatively on the interacted defense spending forecast variable.

More importantly, once exogenous demand fluctuations plus expected future government spending are accounted for, the coefficient on the *PUI* becomes much less negative—its magnitude shrinks to only one-fourth of its previous magnitude and is no longer significant, as shown in Table 4 column 2. On the other hand, the coefficient on the interaction between the *PUI* and the top-quartile-government-sales dummy variable is as negative and significant as before. This indicates that heavy reliance on government demand still renders an industry more cautious in its adjustment of total employees when policy uncertainty is high, over and above what can be accounted for by variations in both past and expected future demand for those industries' output.

Column (3) of Table 4 instead uses contemporaneous growth plus three lags of GDP as controls for aggregate demand conditions, while column (4) uses current and lagged growth of total employment in all private nonfarm industries in a CCE-type estimator à la Pesaran (2006). Either set of aggregate controls is also interacted with the durable-goods industry dummy to account for those industries' greater cyclical variation in output, and hence employment. In column (3), the GI forecast of cumulative GDP growth over the next four quarters is also included. For brevity of presentation, we report only the sum of coefficients on these additional controls based on aggregate economic activity. Note that controls based on the forecast of federal government spending for defense and nondefense purposes over the next four quarters are still included (Table 4, columns 3 and 4).

The growth rates of total private nonfarm payroll interpreted as controls for the unobserved general factors within the framework of CCE-estimators enhance the adjusted R^2 by a fair margin, as shown in Table 4, column 4. By comparison, GDP growth rates contribute no more explanatory power than the two exogenous demand variables alone (Table 4, column 3). Nonetheless, the sum of coefficients on either set of aggregate controls is positive and highly significant, as would be expected. Most of the individual coefficients, not reported, are significant as well. The greater cyclicality of employment in durable-goods industries, measured by the sum of coefficients on the interaction terms with the durable-goods industry dummy, is noticeably smaller when total private payrolls is used as the business-cycle indicator than when GDP is used.[38] This different pattern suggests that swings in total employment in durable-goods industries are more highly correlated with movements in aggregate output but largely just lead movements in aggregate employment (that is, faster changes in durable-goods industries early on are partially reversed later). When aggregate employment is interpreted as a control for the unobserved general factors, the marginally significant coefficients on its interaction with the durable-goods dummy suggest that these industries have somewhat larger loadings than other industries on the unobserved macro factors.

We still include three lags of each industry's own payroll growth in the two regressions reported in columns (3) and (4) of Table 4. The sum of these lagged coefficients is only slightly smaller than in column (1). We omit the recession and recovery dummies from the regression in column (4) because they are all insignificant, which is not surprising, since the total private payroll on the right-hand side fully accounts for the aggregate dynamics of total employment. In contrast, the 2001-recession dummy remains as significant in column (3) as in column (1), whereas the Great Recession dummy is no longer significant. This suggests that employment was, in fact, weaker early in the previous recovery than in this recovery, conditional on output.

The coefficients on the industry-sales-share-weighted forecasts of future four-quarter growth in federal defense and nondefense spending are still negative, but no longer significant in either specification, indicating that these aggregate activity indicators plus the additional control for durable-goods industries' excess cyclicality account adequately for industry-level cyclical dynamics of growth in total employment. The coefficient on the federal defense spending forecast itself remains significantly negative in column (3) of Table 4, which can again be explained by the empirical behavior of defense spending during our sample period, as revealed by the regression results reported in Table 5. That is, as Table 5 shows, the unusually weak employment growth after the 2001 recession coincided with the military build-up to the Iraq war. By comparison, the forecast of cumulative four-quarter growth in GDP is positive but insignificant, while its interaction with the durable-goods-industry dummy is more significant. This seems to suggest that GDP growth in the current and past quarters already contains adequate information as far as the cyclical movement of total employment is concerned, except for those durable-goods industries.

[38] This is because the individual coefficients on the interaction between aggregate employment growth and durable-goods dummy, not reported, switch from positive in the current and last quarters to negative in earlier quarters.

Regarding the main variables of interest, we note that the coefficient on the *PUI* is minuscule in column (4), indicating that controlling for aggregate employment sufficiently accounts for the general effect of policy uncertainty. In contrast, this coefficient remains significantly negative in column (3) and larger in magnitude than that in column (2); that is, total employment is weaker than can be accounted for by output, when policy uncertainty is high. The coefficient on the interacted *PUI* term is in fact slightly more negative than in the regression without any demand or macro controls (in column (1)), and equally significant. These estimates imply that, when policy uncertainty is high, industries in the top quartile in terms of reliance on government purchases limit the number of their number of employees more than other industries and beyond what can be explained by their exposure to the macroeconomy.

We use these estimates to gauge the range of impact on total employment of the heightened uncertainty regarding fiscal policy in recent years. The most conservative estimate is to consider only the cross-industry heterogeneous effect as identified and select the regression that generates the smallest estimate (in absolute value). This corresponds to the coefficient on the interacted *PUI* term in column (1), a regression without any demand or aggregate controls. This estimate would imply that the *PUI* decline of 0.4 point from August to September 2011, just after the height of the debt-ceiling crisis, added about four-tenths of a percentage point to the overall employment growth of those industries selling the most to the federal government. To put this in perspective, the one-year employment growth in September 2011 was only about 2 percent. Counting only the one-month, post-crisis change in the *PUI* again errs on the conservative side, minimizing any influence on the *PUI* from the European turmoil around that time. The index experienced a comparable decline in January of this year from a month ago after the fiscal cliff debate was resolved. In sum, it appears that policy uncertainty has a non-negligible deleterious effect on employment growth even when we adopt the most conservative estimate.

2. Regressions of Production Employment and Average Weekly Hours

We now report estimates of the impact of changing uncertainty on the growth of production employment and on average weekly hours. Instead of reporting all the different specifications considered above for the total number of employees, we examine only the two that arguably produce the most reasonably conservative estimates—based on panel regressions corresponding to equations (1') and (1-CCE) that control for aggregate demand using GDP growth or CCE-type estimators that use growth rates of total private payrolls or average weekly hours to control for unobserved general factors. Again, all the regressions contain industry fixed effects, with standard errors clustered at the industry level.

Table 6 reports the coefficient estimates from a pooled CCE estimator where matched aggregate variables enter as controls for macroeconomic factors that underlie general cross-section dependence. Specifically, for dependent variables (the growth of) total employment, production employment, and average weekly hours, we use the number of all employees, the number of production employees, and average weekly hours of production employees in all private nonfarm industries as the respective aggregate control. We choose these controls, which are stated in terms of weighted average growth across industries, because they correspond to familiar aggregate variables, whereas their unweighted counterparts do not. The consistency of our CCEP estimates likely does not depend on the weights since the necessary rank condition for the unobserved-factor-loading matrix in Pesaran (2006) is likely satisfied given our data and specification.[39] Nonetheless, we conduct robustness tests later. We report the regression result for total employees for comparison purposes. To achieve a meaningful comparison of coefficients for the three dependent variables, we should restrict the sample to be the same set of industries. Among the 77 NAICS industries for which the CES reports data on total employees, eight lack data on production employees and average weekly hours.[40] Hence, we focus on the estimation results using the 69 industries for which data on all three dependent variables are available.

The coefficient estimates for dependent variables (the growth of) total employment, production employment, and average weekly hours are reported in columns (2) through (4), respectively, in Table 6. To further facilitate comparison, in column (1) of Table 6 we reproduce column (4) of Table 4, which contains the coefficient estimates for (the growth of) total employment using all the available data covering the 77 NAICS industries. Comparing columns (1) and (2) of Table 6 reveals that the coefficient on the interaction between the *PUI* and the top-quartile-government-sales dummy variable is somewhat more negative for the subset of industries with data for all three of the labor market indicators. The fit of the regression is also slightly better for the 69-industry subset. Estimates of all the other coefficients are fairly comparable.

Comparisons between columns (2) and (3) show that the dynamics of production employment are rather similar to those of total employment. Some minor differences include: growth of production employment is slightly less persistent at the industry level but somewhat more highly correlated with growth of total private nonfarm production employment. In terms of the two primary coefficients of

[39] Specifically, the rank of the loading matrix equals the number of unobserved factors and does not exceed the number of individual-specific dependent plus independent variables.

[40] The NAICS codes for these eight industries are 61, 312, 316, 482, 483, 487, 521, and 533. See Table A.1 for their names.

interest—on the *PUI* and its interaction with the dummy variable for having a high share of federal government purchases—they are also quite similar, with the latter being a touch more negative for production employment. These patterns suggest that adjustment dynamics for production and nonproduction workers are comparable. They also indicate that our finding of policy uncertainty being more detrimental to industries relying especially heavily on federal government demand is reasonably robust.

Comparing columns (2) or (3) with column (4) in Table 6 indicates that the dynamics of average weekly hours are markedly different. The most noticeable difference may be the much poorer fit of the regression. This is probably not surprising: Figure 4 offers a strong hint that fluctuations in average hours contain more high-frequency noise and are less cyclical. Low persistence of the average hours process is reflected in the vanishingly small coefficients on its own lags, so only one lag is included. Similarly, only the contemporaneous growth of all private nonfarm industry average hours is included because coefficients on all the lags are negligible. One coefficient significantly different from its counterparts for employees is on the additional aggregate control for durable goods industries. It appears that average hours are substantially more cyclical for these industries than for the others. Another difference is that average hours seem more positively correlated with forecasts of government defense demand, suggesting that firms rely relatively more on adjusting the intensive margin for labor input during downturns. More importantly, neither of the coefficients related to the *PUI* is significant, consistent with our conjecture that policy uncertainty should have no direct impact on average hours, although it makes little difference whether the associated extensive labor margin—production employment—is controlled for.

The CCEP regressions underlying Table 6 weight each industry equally, which is the standard treatment in WG pooled regressions. As a robustness check, we examine a weighted version of the same regression specifications. Weighting becomes necessary if the rank condition of the factor-loading matrix is not satisfied, and Pesaran (2006) shows that applying the same weights used to construct the aggregate controls to the regression ensures consistency. Hence we apply the weights underlying the aggregate controls—growth rates for all private nonfarm (PNF) industries—to the pooled regressions. Since fixed weights are called for, we weight each industry in the total-employee-growth regression by its average level of total employment over the sample period, and by its sample average production employment in the other two regressions. This is because employment growth in any subset of industries (denoted n_t) equals the employment-weighted (denoted ω_{it}) average of industry growth (denoted n_{it}):

$$n_t = \ln\left(1+\frac{\Delta N_t}{N_{t-1}}\right) \doteq \frac{\Delta N_t}{N_{t-1}} = \frac{\sum_i N_{it}}{\sum_i N_{i,t-1}} - 1 = \sum_i \left(\frac{N_{i,t-1}}{\sum_i N_{i,t-1}} \frac{N_{it}}{N_{i,t-1}}\right) - 1 = \sum_i \left(\omega_{i,t-1} \frac{N_{it}}{N_{i,t-1}}\right) - 1 \doteq \sum_i \omega_{i,t-1} n_{it}.$$

n_t is as defined above. N_t (N_{it}) is the number of employees across all PNF industries (in industry *i*). Since employee shares across industries are highly correlated over time and their changes are little correlated with the *PUI*, using the average share over the sample period as the weight satisfies the consistency requirement as derived in Pesaran (2006).[41] By comparison, average weekly hours for all PNF industries depend on industry share of both production employees and total hours:

$$h_t = h_t^T - n_t \doteq \sum_i \omega_{i,t-1}^H h_{it}^T - \sum_i \omega_{i,t-1} n_{it} \ ,$$

where h_t^T (h_{it}^T) is the growth rate of total hours for all PNF industries (industry *i*), and $\omega_{i,t-1}^H$ is the *i*'s share in total hours. The bulk of the dispersion in total hours across industries is due to the dispersion in the number of production employees. Therefore, for simplicity, we use industry average counts of production employees as weights in the average-hour regression.

Estimates from these weighted regressions are reported in Table B.2 in Appendix B. The primary coefficient of interest—on the interaction between the *PUI* and high-sales-to-government dummy variable—remains equally significant in the employee-growth regressions although the (absolute) magnitude diminishes slightly (and insignificantly). This result seems intuitive in that the industries with high shares of output sold to the government are down-weighted in these regressions, since they tend to be goods-producing industries with less than equal-weighted-average employee share. Nevertheless, it continues to hold that industries relying most heavily on government demand are more sensitive to changes in policy uncertainty. At the same time, this coefficient remains insignificant in the average-hours regression. Likewise, the coefficients on the *PUI* itself are still insignificant in all the regressions. The other coefficients also remain qualitatively the same, by and large.[42]

As another related robustness check, we estimate an equal-weighted CCEP regression where the controls to proxy for unknown macro factors are simple averages of the dependent and industry-specific independent variables. The result is reported in Table B.3 in Appendix B. It is apparent that all the

[41] The cross-industry correlations of employee shares in 1998:Q1 (beginning of the sample), 2013:Q1, and the average over the period are all above 0.94.

[42] Except for those related to nondefense government spending growth in the employee regressions. Now nondefense spending has a positive uniform impact across industries but a negative impact on those industries relying more on government demand for nondefense purposes. This is likely because, among this subset of industries, those with relatively high employee shares exhibit more cyclical fluctuations in employees, which load negatively on (countercyclical) nondefense government spending.

coefficient estimates are extremely similar to the baseline estimates reported in Table 6, including the primary coefficient of interest—on the *PUI* interaction term. This again confirms that findings in the baseline specification are fairly robust and not due to its particular construction of aggregate controls.

As yet another, more stringent, robustness check, we apply the CCE mean-group estimator, which averages across industries coefficient estimates from the same regression run separately by industry. The "same" excludes the industry-aggregate-variable interaction terms, such as the *PUI* interacted with the high-industry-sales-to-government dummy variable, since the coefficient on every aggregate variable is allowed to vary freely across industries. As Pesaran and Smith (1995) show, the MG estimator produces consistent estimates for dynamic panels with heterogeneous slope coefficients, in which case the pooled estimator tends to bias upward the autoregressive (AR) coefficients on the dependent variable and bias downward the other coefficients.[43] The CCEMG estimator further controls for general (unknown) cross-sectional dependence.

We now compare these coefficient estimates, reported in Table 7, with their counterparts in the same column in Table 6. Consistent with derivations in Pesaran and Smith (1995), the MG estimates of (the sum of) AR coefficients of dependent variables are uniformly lower, while estimates of the coefficient on the *PUI* are uniformly higher—less negative. In fact, the coefficient on the *PUI* becomes insignificant for the two employee regressions for the 69 industries that have data for all three variables. This suggests that the overall magnitude and the significance of the impact of changes in policy uncertainty is likely overstated by pooled dynamic panel regressions, which restrict slope coefficients to be the same across industries. Moreover, as shown in Figure 7, most industry-specific *PUI* estimates are not significant, which is hardly surprising given the much smaller number of degrees of freedom in each time-series regression by industry.

On the other hand, our identification strategy hinges on the cross-industry *differential* negative impact of *PUI* fluctuations, which we posit to be correlated with an industry's reliance on government demand. In other words, the higher the share of an industry's output sold to the federal government, the more negative the coefficient on the *PUI* we would expect. We therefore regress the *PUI* coefficient by industry on the average of the industry share of sales to the federal government over the sample period. To match the above pooled regression estimates more closely, we also regress the *PUI* coefficient on the dummy variable that marks those industries in the top quartile in terms of the share of sales to the federal

[43] The AR coefficient is biased upward when regressors are positively autocorrelated, which is more likely, and vice versa.

government. We examine only the 69 industries for which the industry-average *PUI* coefficient is insignificant. The coefficient estimates are reported in Table 8, Panel A and B, respectively.[44] The reactions of total as well as production employees to *PUI* shocks both exhibit a significantly negative correlation with the (average) share of industry sales to the federal government. In contrast, the reaction of average hours to the *PUI* is insignificantly correlated with this share.

To help visualize the relationship, Figure 7 presents the scatterplot of the first regression for total employees (Panel A) and production employees (Panel B), along with the fitted regression lines. The *PUI* coefficient is on the vertical axis and the average share is on the horizontal axis. The negative relationship between the two variables is clearly not driven by outliers. Marked in red are the industry-specific *PUI* coefficients that are significant. This figure thus also reveals that, while most industry-specific *PUI* estimates are not significant, the significant ones tend to be negative and associated with industries with relatively high shares of sales to the federal government. This helps to explain why the pooled estimates of the coefficient on the *PUI* is significantly negative. In sum, this cross-sectional pattern of differential coefficients on the *PUI* confirms that the *PUI* does not merely reflect other macro factors responsible for aggregate fluctuations. Instead, it contains a distinct aggregate factor related to perceived uncertainty regarding fiscal policy.

We also experiment with using GDP growth, both past realizations and future forecasts, as controls for macroeconomic conditions for the same set of dependent variables. Table B.4 in Appendix B reports the coefficient estimates. The coefficients on the common set of variables are qualitatively similar. In particular, the dynamics of the two measures of the number of employees are fairly similar.[45] Just as in the above case with aggregate employment as controls, the coefficient on the interaction term between the *PUI* and the dummy variable signifying a high fraction of sales ultimately to the federal government is more negative, albeit insignificantly so, for the narrower set of industries. Likewise, this coefficient is noticeably more negative for production employees than for total employees, and essentially zero for average hours. To get a sense of the magnitude, a *PUI* decline of 0.4 point (comparable to the change in from August to September 2011) would add a little over one extra percentage point to the growth of production employment in the industries in the top quantile in terms of share of sales to the federal government.

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[44] Since it is the dependent variables that contain estimation errors in addition to sampling errors, the coefficient estimates are unbiased, but their standard errors are larger because of the estimation errors.

[45] Again, for ease of comparison, column (1) reproduces column (3) of Table 4, the regression result for total employees, based on the broader set of 77 NAICS industries for which data are available.

On the other hand, the coefficient on the *PUI* itself is insignificantly different from zero for the number of production employees, but significantly negative for average hours. The former is consistent with the definition of these employees—directly engaged in generating current output—which implies that common movements in the number of these employees should be better accounted for by aggregate output (GDP) than those for nonproduction employees, and in turn, total employees. The uniformly negative impact of the *PUI* on average hours across all industries, however, is inconsistent with the prior that pure second-moment shocks should not directly affect average hours, a variable that is not subject to adjustment cost. One plausible explanation is that, as discussed in Section II, the reported number of average hours worked is confounded by changes in the mix of full-time versus part-time employees and thus affected by changes in uncertainty as well. Another possibility is that the *PUI* series used, based largely on expressed sentiment of uncertainty, captures not only uncertainty but also macro factors that fluctuate at higher-than-business-cycle frequency. This is consistent with the result that GDP growth rates, realized or forecast, matter little for average hours. On the other hand, as in the previous set of panel regressions underlying Table 6, growth in average hours is positively correlated with forecasts of government demand, in contrast with the slight negative correlation of growth in total as well as production employment with forecasts of government demand.[46] Consistent with the interpretation that firms rely relatively more on adjusting the intensive margin for labor input during bad times, coefficients on the dummy variables for the Great Recession and the subsequent recovery are both significantly positive.

Last, we also experiment with including up to two lags of the *PUI* in addition to the current-period value in the regressions reported in Tables 6 and B.4 (with the aggregate measure corresponding to the dependent variablea and GDP, respectively, as controls for macro factors). The corresponding regression results are reported in Tables B.5 and B.6 in Appendix B. In general, the sum of coefficients on both current and lagged *PUI*s is more negative than that on the current value alone as reported in the corresponding column in Tables 6 and B.4, respectively. The same pattern is observed for the coefficients on the interaction between the *PUI* and the dummy variable for those industries in the top quartile ranked by the share of sales to the federal government. Coefficients on the other variables are fairly comparable. This confirms the observation that the finding of a negative impact of policy uncertainty is not reversed quickly.

[46] The sum of coefficients on interactions between lagged GDP growth and the durable-goods dummy variable is insignificant because the positive first lag is cancelled out by negative farther lags.

To sum up the findings for the full set of NAICS industries with data for all three of the labor market indicators, increases in policy uncertainty cause the growth of production employment and, in turn, total employment to slow more in industries that are ranked in the top quartile in terms of the share of their output sold to the federal government. The estimated magnitude of this extra negative impact ranges from slightly below one-half to somewhat above one percentage point during the major episodes of spikes in policy uncertainty since the Great Recession, such as the debt-ceiling crisis in August 2011. By comparison, changes in policy uncertainty seem to show no differential impact on average weekly hours across industries, consistent with the prior suggested by theory.

3. Regressions Controlling for Industry-Specific Output—the IP Industries

Table 9 presents estimates from the panel regressions using the subset of industries whose monthly output data are reported in the Federal Reserve's IP database. We omit the utilities sector because its production process is heavily regulated. Among the remaining industries—essentially all manufacturing—we also omit sector 3364OT (other transportation equipment) as we did in the previous set of regressions, because of its extreme value in terms of the share of sales to the federal government. Its inclusion leads to slightly more negative coefficients on basically all the *PUI*-related terms, although the differences in coefficient estimates are generally small and insignificant.

As explained above, controlling for the industry-specific output should in principle yield a more conservative specification. We use total employees as the case study to investigate how much the difference in specification affects the coefficients on the *PUI*-related terms.[47] Column (1) in Table 9 reports the estimates from the same regression for total employees as that underlying columns (1) and (2) in Table 6 but only for the 18 IP industries. In other words, it controls for aggregate output (that is, GDP) growth but not for industry-specific output growth.[48] The coefficients on the *PUI* and its interaction with the high-sales-to-government dummy variable in column (1) here are both less negative than their counterparts in Table 6, although neither difference is statistically significant. The milder adverse impact, both the baseline and the cross-industry differential, of higher policy uncertainty on employees in manufacturing than on employees in the other industries may be due to lower employment adjustment

[47] Corresponding results for production employees and average weekly hours are reported in Table B.7 in Appendix B. Most coefficients are qualitatively comparable with the regressions with industry output controls.

[48] We omit from the table those coefficients from regression (1) not included in regressions (2) to (4). Estimates from the same regressions as those underlying Table 7, that is, controlling for GDP growth, are generally rather similar.

costs in manufacturing. This would be consistent with the theory proposed in Barsky and Miron (1989) that industries characterized by greater seasonal or cyclical fluctuations would optimally choose technologies that feature flatter marginal cost curves as well as lower adjustment costs.

Comparing columns (1) and (2) in Table 9, both for total employees, reveals that controlling for industry output improves the overall fit slightly, as would be expected. It, however, leads to a less negative and only marginally significant coefficient on the interaction between the *PUI* and the high-sales-to-government dummy variable. The uniform baseline negative effect of increases in the *PUI* is also weaker. At the same time, industry output data enable us to test whether greater policy uncertainty blunts the response of employment to output fluctuations, especially for those industries that rely most heavily on government demand. The essentially zero coefficient on the interaction between industry output growth and the *PUI* indicates that this effect is generally absent. It is, however, present for those industries selling relatively high shares of their output to the federal government, as evidenced by the marginally significant negative coefficient on the triple interaction term, although the magnitude is miniscule. If we use the change in the *PUI* around the debt-ceiling strife in 2011, for example, which was about 0.4 point, then employment in those industries in the top quartile in terms of the share of sales attributed to government would increase by a mere one basis point less for every 1 percent growth in output in the same period. By comparison, output growth of 1 percent coincides with employment growth of 0.15 percent in terms of the average contemporaneous relationship.

Comparisons of coefficients for total employment growth (column (2)) versus those for production employment growth (column (3)) indicate that the output-independent adverse impact of higher policy uncertainty is stronger for production employees than for total employees, while the output-dependent impact is weaker. This seems consistent with the distinction between the two types of workers: for any given increase in output needed, the option value of waiting is likely higher on net for nonproduction workers and in turn for total employees than for production workers, who contribute to current output directly. One feature common to columns (1) through (3) of Table 9 is the significantly negative coefficients on the 2001-recession dummy variable, signifying that employment in manufacturing was exceptionally weak in that downturn conditional on either aggregate or industry output growth. By comparison, employment behaved more or less as usual during the Great Recession, once we account for the extraordinary decline in output. Since then, manufacturing output has grown at a more robust pace than GDP, and thus growth in employment no longer appears especially strong once we control for industry output growth. One result common to columns (1) and (2) is that growth in the number of employees loads more negatively on forecasts of federal spending when only industry but not aggregate output growth is controlled for.

Column (4) reports estimates for average weekly hours. The difference between its dynamics and those of employees for the IP industries resembles that for all industries in Table 7, so we remark only on the two new coefficients concerning the impact of policy uncertainty on the adjustment of the number of employees in response to a given rate of output growth. It appears that average hours responds more positively to output growth when policy uncertainty is high. This is consistent with Bloom et al. (2007) reviewed above: firms resort more to the intensive margin and less to the extensive margin for adjusting labor input when they face greater uncertainty. This effect is estimated to be smaller for those industries selling more of their products to the government, although the difference is insignificant. One explanation that can account for the output-dependent effect of policy uncertainty on both employees and average hours hinges on a changing composition of full- versus part-time employees. For both employment and average hours in the high-sales-to-government industries to be less sensitive to output growth when uncertainty is high, it may be that they both add fewer employees on net and shift toward part-time employees.

In short, for the (manufacturing) industries in the IP database, controlling for each industry's own output growth appears to make only a minor difference for most coefficients, particularly those concerning the impact of policy uncertainty on the growth of emploment and average weekly hours. This suggests that our findings from earlier regressions covering the full set of industries are likely to be reasonably robust despite the lack of industry-specific output data. Moreover, whatever bias there may have been in earlier regressions because of the dynamic panel specification also seems mild, especially concerning the coefficients of interest—those related to the effect of policy uncertainty. Most important for our purpose is, of course, the finding that increased policy uncertainty deters firms from adding employees on net and that the larger the share of their output sold to the federal government, the more reluctant they become. Note that this deleterious effect is on the net flow of employment, allowing for the likely offsetting effect from a lower rate of voluntary separations due to greater caution on the part of employees.

VI. Concluding Remarks

To summarize, using quarterly industry employment data, we find evidence that high levels of policy uncertainty retard employment growth. In particular, industries selling a relatively high fraction of their output directly and indirectly to the federal government tend to slow their payroll growth more than other industries when policy uncertainty is elevated, even after accounting for industry demand conditions. Moreover, this effect is nontrivial economically, although it is insufficient to fully account for the unusually slow employment growth during the Great Recession and the subsequent recovery. By comparison, the adverse effect of elevated policy uncertainty differs little across industries. There is also some indication that policy uncertainty exerts a negative across-the-board influence on growth in both the number of employees and average weekly hours above and beyond what can be accounted for by output growth.

We also find evidence, albeit not particularly robust, that increased policy uncertainty blunts firms' adjustment of the number of employees, especially those not directly engaged in current production, in response to changes of their own output in those manufacturing industries that sell a relatively high share of output directly and indirectly to the federal government. By comparison, average weekly hours become more responsive to output changes in all these industries when policy uncertainty is high. This is consistent with what some theories would predict: firms adjust labor input more along the intensive than the extensive margin when faced with heighted uncertainty because of the adjustment costs associated with the latter.

One implication of these findings is that the government shutdown and debt-ceiling showdown in October have probably created non-negligible drag on the economy in large part because these events raised policy uncertainty yet again. Gyrations of stock prices around the few days when tense negotiations took place on Capitol Hill offer tangible proof of the deleterious impact of policy uncertainty. Moreover, further harm to the economy will likely result from continuing political wrangling, since the perception of uncertainty remains elevated, given that the debt ceiling was lifted only temporarily as was the extension of funding for the federal government. The most recent bipartisan budget agreement funds the federal government through the 2014 fiscal year. It does not, however, raise the debt ceiling, and thus the specter of another default scare early next year remains. Additional damage will be inevitable if the political disagreement is not resolved in time.

Furthermore, heightened fiscal uncertainty may well drive up Treasury yields, especially at the longer end, even without another downgrade of the U.S. government's credit rating. Higher Treasury yields will pass through to yields on private debt, resulting in a higher cost of capital for businesses and consumers. Greater fiscal uncertainty can further induce a general perception of uncertainty about the overall economy, which tends to drive up the risk premium on private sector claims such as corporate bonds and stocks. For instance, simple regressions reveal a high correlation between spreads on corporate bonds over Treasuries and the policy uncertainty index compiled by Baker et al. (2013). All of these forces of restraint on the macroeconomy will mean that full employment will be reached later than otherwise, especially since monetary policy, already constrained by the zero lower bound, may not be able to provide sufficient additional stimulus to offset the restraints.

In fact, the detrimental effect of greater policy uncertainty on the aggregate economy may well exceed the magnitude estimated in this study. In particular, this is because employment is a net outcome between the gross flows of hiring and separation. To the extent that workers also become more cautious, and thus less likely to look for new jobs and then quit when policy uncertainty is perceived to be high, the lower rate of separation at least partially offsets the lower rate of hiring due to caution on the part of employers. This then results in a smaller change in the net flow—employment. In contrast, investment is a gross flow, and any increase in funding cost will matter more for investment than for employment. All told, the impact of policy uncertainty on business investment is likely to be more pronounced. Besides, studies such as Bloom (2009) suggest that another detrimental by-product of a diminished pace of resource reallocation (through employee turnover and investment, for instance) is slower productivity growth because resources cannot be directed to the most efficient use quickly.

There are certainly other ways in which firms' exposures to fiscal policy uncertainty differ. For example, industries that receive more government subsidies are likely to become more cautious when the policy outlook is more uncertain. Also, taxes on capital affect the cost of capital, and they likely matter more for industries that are more capital intensive. These issues will be worth exploring in future analyses.

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Table 1. Share of industry output sold directly and indirectly to meet federal *defense* final demand (%)

Industry Name	1998	2002	2007	2011
Other transportation equipment	19.5	**27.0**	27.5	34.0
Computer systems design and related services	5.4	**10.3**	16.4	22.5
Computer and electronic products	4.1	**7.8**	9.2	13.1
Miscellaneous professional, scientific, and technical services	5.5	**7.6**	8.6	10.0
Information and data processing services	4.2	**6.3**	7.2	8.8
Printing and related support activities	4.2	**5.1**	6.3	6.7
Oil and gas extraction	4.6	**5.1**	6.0	6.2
Fabricated metal products	*3.0*	**5.0**	6.1	7.9
Publishing industries (includes software)	4.5	**4.8**	5.3	*6.0*
Administrative and support services	*3.2*	**4.6**	5.3	*5.4*

Source: Author's calculations.

Table 2. Share of industry output sold directly and indirectly to meet federal *nondefense* final demand (%)

Industry Name	1998	2002	2007	2011
Other transportation equipment	8.4	**8.3**	7.9	7.8
Computer systems design and related services	2.9	**7.5**	7.1	8.5
Computer and electronic products	2.6	**4.3**	5.7	7.4
Miscellaneous professional, scientific, and technical services	2.9	**4.2**	4.1	4.9
Information and data processing services	2.2	**3.5**	3.4	4.3
Printing and related support activities	2.4	**2.9**	2.9	*3.1*
Oil and gas extraction	*1.8*	**2.8**	3.0	4.1
Fabricated metal products	2.4	**2.7**	2.6	*2.9*
Publishing industries (includes software)	*1.4*	**2.6**	*2.2*	*2.2*
Administrative and support services	*1.7*	**2.6**	2.5	*2.7*

Source: Author's calculations.

Table 3. Unconditional Correlations among Variables over the Sample Period (1998:Q1–2013:Q1)

	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)
(I) Forecast, GDP Next 4 Quarters	1						
(II) Forecast, Fed. Gov. Defense Spending Next 4 Quarters	0.47	1					
(III) Forecast, Fed. Gov. Nondefense Spending Next 4 Quarters	0.129	0.595	1				
(IV) Policy Uncertainty Index	-0.329	-0.431	-0.228	1			
(V) GDP 4-Quarter Average	0.45	-0.052	-0.354	-0.449	1		
(VI) Industry Employment	0.111	-0.18	-0.252	-0.1	0.327	1	
(VII) Total Private Employment	0.396	-0.355	-0.526	-0.29	0.824	0.403	1

Notes: All variables other than the Policy Uncertainty Index are annualized rates of quarterly growth, unless the horizon is specified otherwise. All forecasts are produced by Global Insight.
Source: Author's calculations.

Table 4. Panel regression estimates: dependent variable = quarterly growth of total employees

VARIABLES	(1) **Own Lags Only**	(2) **Own Lags + Demand Control**	(3) **Own Lags + GDP**	(4) **Own Lags + Total Empl., CCE-estimator**
PUI	**-2.160*** **	**-0.505**	**-1.317*** **	**-0.0569**
	[0.385]	**[0.441]**	**[0.464]**	**[0.225]**
High government purchase share * PUI	**-1.108*** **	**-1.546*** **	**-1.588*** **	**-1.622*** **
	[0.359]	**[0.410]**	**[0.537]**	**[0.484]**
Sum of 3 lags of own employment growth	0.503***	0.419***	0.440***	0.432***
	[0.058]	[0.079]	[0.074]	[0.082]
Sum of Total private employment or GDP growth (t-3 to t)			0.279***	0.465***
			[0.057]	[0.076]
Sum of Durable dummy * Total empl. or GDP growth (t-3 to t)			0.403***	0.215*
			[0.114]	[0.115]
GI forecast of GDP growth over next 4 quarters			0.211	
			[0.164]	
Durable*GI forecast of GDP growth over next 4 quarters			0.461**	
			[0.182]	
Sum of lags of defense growth * defense share		0.860**		
		[0.394]		
Sum of lags of defense growth		-0.002		
		[0.027]		
Sum of lags of exports growth * export share		0.651***		
		[0.166]		
Sum of lags of exports growth		-0.002		
		[0.036]		
Export share		10.31***		
		[3.056]		
GI forecast of fed. gov. defense growth over next 4 quarters * Government defense purchase share in output		-2.601**	-1.100	-1.431
		[1.239]	[1.186]	[1.139]
GI forecast of fed. gov. nondefense growth over next 4 quarters * Gov. nondefense purchase share in output		-3.639	-3.735	-3.135
		[2.541]	[2.359]	[2.263]
GI forecast of fed. gov. defense spending growth over next 4 quarters		-0.0974	-0.132**	-0.0523
		[0.0638]	[0.0580]	[0.0541]
GI forecast of fed. gov. nondefense spending growth over next 4 quarters		0.0388	0.0917	0.0337
		[0.0693]	[0.0676]	[0.0659]
Government purchase share in output	-2.799	-3.382	0.950	-2.159
	[5.712]	[4.076]	[8.349]	[6.233]
2001 recession dummy	-2.973***	-1.694***	-2.302***	
	[0.548]	[0.572]	[0.533]	
2008-9 recession dummy	-2.858***	-3.144***	-0.941	
	[0.498]	[0.566]	[0.735]	
Post-2009 recovery dummy	2.516***	0.0429	1.811**	
	[0.425]	[0.795]	[0.722]	
Constant	2.754***	0.209	0.314	0.576
	[0.473]	[0.657]	[0.667]	[0.471]
Observations	4,697	4,466	4,697	4,697

R-squared	0.281	0.306	0.303	0.316
Adjusted R-squared	0.279	0.300	0.299	0.313
Number of NAICS code	77	77	77	77
Quarters per NAICS code	61	58	61	61

Notes: All growth rates are annualized rate. Robust standard errors in brackets. *** p < 0.01, ** p < 0.05, * p < 0.1.

Source: Author's calculations.

Table 5. Relationship between payroll growth of all private nonfarm industries and forecasts

LHS: Total private payroll growth	Coefficient	Std. Error	t
GDP 4-Quarter Average	0.667***	0.073	9.18
Forecast, GDP Next 4 Quarters	0.868***	0.191	4.54
Forecast, Fed. Gov. Defense Spending Next 4 Quarters	-0.339***	0.063	-5.41
Forecast, Fed. Gov. Nondefense Spending Next 4 Quarters	-0.083	0.059	-1.42
Constant	-2.691***	0.439	-6.14

Notes: *** p < 0.01, ** p < 0.05, * p < 0.1.
Source: Author's calculations.

Table 6. Common-correlated-effects (CCE) panel estimators for quarterly growth of employees and average weekly hours, with the corresponding aggregate indicators as controls for unobserved general factors

VARIABLES	(1) Total employees, All Industries	(2) Total employees, Matched Sample	(3) Production Employees	(4) Average Weekly Hours
PUI	**-0.0569**	**0.112**	**0.420**	**0.170**
	[0.225]	**[0.207]**	**[0.334]**	**[0.333]**
High government purchase share * PUI	**-1.622*** **	**-1.909*** **	**-2.574*** **	**-0.277**
	[0.484]	**[0.438]**	**[0.583]**	**[0.532]**
Sum of lags of own growth (3 for employees, 1 for hours)	0.432***	0.517***	0.440***	-0.049
	[0.082]	[0.052]	[0.058]	[0.041]
Sum of Total private prod. employees or hours growth (t-3 to t for employees, t for hours)	0.465***	0.410***	0.543***	0.536***
	[0.076]	[0.059]	[0.077]	[0.110]
Sum of Durable dummy * Total empl. or hours growth (t-3 to t for employees, t for hours)	0.215***	0.123***	0.207***	1.184***
	[0.115]	[0.092]	[0.106]	[0.340]
Production employees growth (t)				0.0364
				[0.0258]
GI forecast of fed. gov. defense spending growth over next 4 quarters * Government defense purchase share in output	-1.431	-1.439	-1.077	1.382*
	[1.139]	[1.167]	[1.240]	[0.780]
GI forecast of fed. gov. nondefense spending growth over next 4 quarters * Gov. nondefense purchase share in output	-3.135	-2.802	-3.750	-0.117
	[2.263]	[2.145]	[2.642]	[1.573]
GI forecast of fed. gov. defense spending growth over next 4 quarters	-0.0523	-0.0417	-0.0339	0.0131
	[0.0541]	[0.0547]	[0.0630]	[0.0438]
GI forecast of fed. gov. nondefense spending growth over next 4 quarters	0.0337	0.0350	0.0618	-0.0516
	[0.0659]	[0.0637]	[0.0716]	[0.0465]
Government purchase share in output	-2.159	5.239	6.427	3.413
	[6.233]	[4.515]	[5.921]	[3.431]
Constant	0.576	0.185	-0.206	-0.0398
	[0.471]	[0.373]	[0.567]	[0.384]
Observations	4,697	4,209	4,209	4,209
R-squared	0.316	0.405	0.339	0.050
Adjusted R-squared	0.313	0.402	0.335	0.047
Number of NAICS code	77	69	69	69
Quarters per NAICS code	61	61	61	61

Notes: All growth rates are annualized rate. Each column header denotes the dependent variable and the industries in the sample when relevant. Robust standard errors in brackets. *** p < 0.01, ** p < 0.05, * p < 0.1.
Source: Author's calculations.

Table 7. Common-correlated-effects (CCE) mean-group (MG) estimators for quarterly growth of employees and average weekly hours

VARIABLES	(1) Total Employees, All Industries	(2) Total Employees, Matched Sample	(3) Production Employees	(4) Average Weekly Hours
PUI	**-0.610****	**-0.355**	**-0.276**	**-0.0752**
	[0.280]	**[0.251]**	**[0.367]**	**[0.267]**
Sum of lags of own growth (3 for employees, 1 for hours)	0.228***	0.247***	0.251***	-0.130***
	[0.047]	[0.050]	[0.048]	[0.0190]
Sum of Total private prod. employees or hours growth (t-3 to t for employees, t for hours)	0.674***	0.682***	0.722***	0.729***
	[0.072]	[0.077]	[0.078]	[0.120]
Production employees growth (t)				0.0305
				[0.0237]
GI forecast of fed. gov. defense spending growth over next 4 quarters	-0.0745**	-0.0768**	-0.0637	0.0418
	[0.0320]	[0.0338]	[0.0422]	[0.0398]
GI forecast of fed. gov. nondefense spending growth over next 4 quarters	-0.0208	-0.0228	-0.0223	-0.0951***
	[0.0371]	[0.0349]	[0.0417]	[0.0341]
Constant	0.586	0.305	0.115	0.298
	[0.458]	[0.428]	[0.565]	[0.362]
Observations	4,697	4,209	4,209	4,209
R-squared	0.593	0.623	0.584	0.253
Adjusted R-squared	0.469	0.509	0.457	0.085
Number of NAICS code	77	69	69	69
Quarters per NAICS code	61	61	61	61

Notes: All growth rates are annualized rate. Each column header denotes the dependent variable and the industries in the sample when relevant. Every coefficient is the simple average of industry-specific estimates. The number of observations refers to the full panel. Robust standard errors in brackets. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Source: Author's calculations.

Table 8. Cross-section relationship between the CCEMG estimates of the industry-specific coefficients on *PUI* and measures of industry reliance on federal government final demand

Panel A: Industry reliance measured by the share of its sales accounted for by the federal government (averaged over the sample period)

VARIABLES	(1) **Total Employees**	(2) **Production Employees**	(3) **Average Hours**
Avg. share of industry sales to federal government	-22.68***	-26.84***	-10.13
	[6.669]	[7.216]	[6.698]
Observations	69	69	69
R-squared	0.119	0.106	0.024
Adjusted R-squared	0.074	0.092	0.010

Panel B: Industry reliance measured by a dummy variable that equals one for industries in the top quartile in terms of share of its sales accounted for by the federal government

VARIABLES	(1) **Total Employees**	(2) **Production Employees**	(3) **Average Hours**
High industry share of sales to federal government	-2.178***	-2.404***	-1.022
	[0.609]	[0.823]	[0.624]
Observations	69	69	69
R-squared	0.115	0.089	0.026
Adjusted R-squared	0.102	0.075	0.011

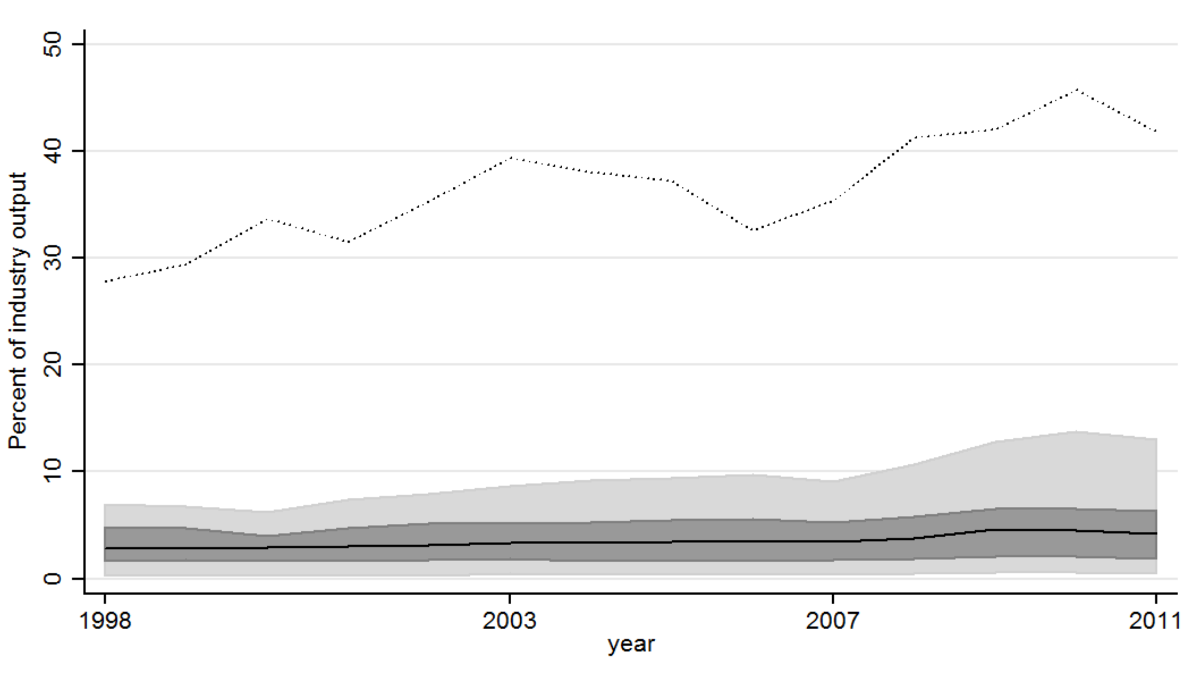
Notes: Robust standard errors in brackets. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Source: Author's calculations.

Table 9. Panel regression estimates for quarterly growth of employees and average weekly hours, IP industries only to control for industry own output growth

VARIABLES	(1) Tot. employees, No Output	(2) Total employees	(3) Production Employees	(4) Average Weekly Hours
PUI	**-2.114*** **	**-1.010***	**-1.499** **	**-1.817***
	[0.693]	**[0.569]**	**[0.687]**	**[0.912]**
High government purchase share * PUI	**-0.976** **	**-0.870***	**-1.753***	**-0.509**
	[0.449]	**[0.486]**	**[1.005]**	**[0.400]**
Output growth (t) * PUI		**0.00341**	**0.0184**	**0.0540** **
		[0.0215]	**[0.0377]**	**[0.0251]**
Output growth (t) * PUI * High gov. purchase share		**-0.0257***	**-0.0257**	**-0.0274**
		[0.0137]	**[0.0186]**	**[0.0226]**
Sum of output growth (GDP: t-3 to t; industry own: t-6 to t)	0.313***	0.424***	0.429***	-0.006
	[0.113]	[0.054]	[0.084]	[0.058]
Sum of Durable dummy * GDP growth (t-3 to t)	0.383***			
	[0.107]			
Log(output) - log(employment) (t-1)		1.766	5.690***	
		[1.094]	[1.791]	
Production employee growth (t)				-0.0128
				[0.0794]
GI forecast of fed. gov. defense growth over next 4 quarters * Gov. defense purchase share in output	1.900*	0.308	1.109	1.744
	[0.993]	[0.951]	[0.935]	[1.003]
GI forecast of fed. gov. nondefense growth over next 4 quarters * Gov. nondefense purchase share in output	-4.665	-4.982	-5.631	-3.297
	[3.186]	[2.937]	[3.824]	[2.655]
GI forecast of fed. gov. defense spending growth over next 4 quarters	-0.187**	-0.261**	-0.349***	0.0959
	[0.0650]	[0.109]	[0.0981]	[0.0873]
GI forecast of fed. gov. nondefense spending growth over next 4 quarters	0.207**	0.0170	-0.0130	0.123
	[0.0888]	[0.0886]	[0.109]	[0.120]
Government purchase share in output	13.59*	9.946	-2.535	6.182
	[6.844]	[12.08]	[19.36]	[4.875]
2001 recession dummy	-2.111***	-3.184***	-3.814***	0.168
	[0.522]	[0.723]	[0.723]	[0.595]
2008-9 recession dummy	0.797	-0.0160	-0.667	0.367
	[0.948]	[0.688]	[0.707]	[0.677]
Post-2009 recovery dummy	4.327***	1.180	0.619	3.155***
	[1.322]	[0.745]	[0.806]	[0.819]
Constant	-3.113***	-1.421*	0.585	0.889
	[0.495]	[0.805]	[1.336]	[0.661]
Observations	1,098	1,098	1,098	1,098
R-squared	0.589	0.634	0.552	0.243
Adjusted R-squared	0.579	0.627	0.544	0.229
Number of BEA industry code	18	18	18	18
Quarters per BEA industry code	61	61	61	61

Notes: All growth rates are annualized rate. Each column header denotes the dependent variable and output control used. Robust standard errors in brackets. *** p < 0.01, ** p < 0.05, * p < 0.1.
Source: Author's calculations.

Figure 1a. Cross-industry distribution of each industry's share of direct plus indirect sales to the federal government: 1998 to 2011



Notes: the solid line depicts the median industry in terms of output share accounted for by direct plus indirect sales to the federal government, the dark shaded area depicts the inter-quartile range across industries, the light shaded area depicts the 10th to the 90th percentile, while the top (dotted) line depicts the value for the industry with the highest share.
Source: Author's calculations.

Figure 1b. Share of federal government expenditures in GDP

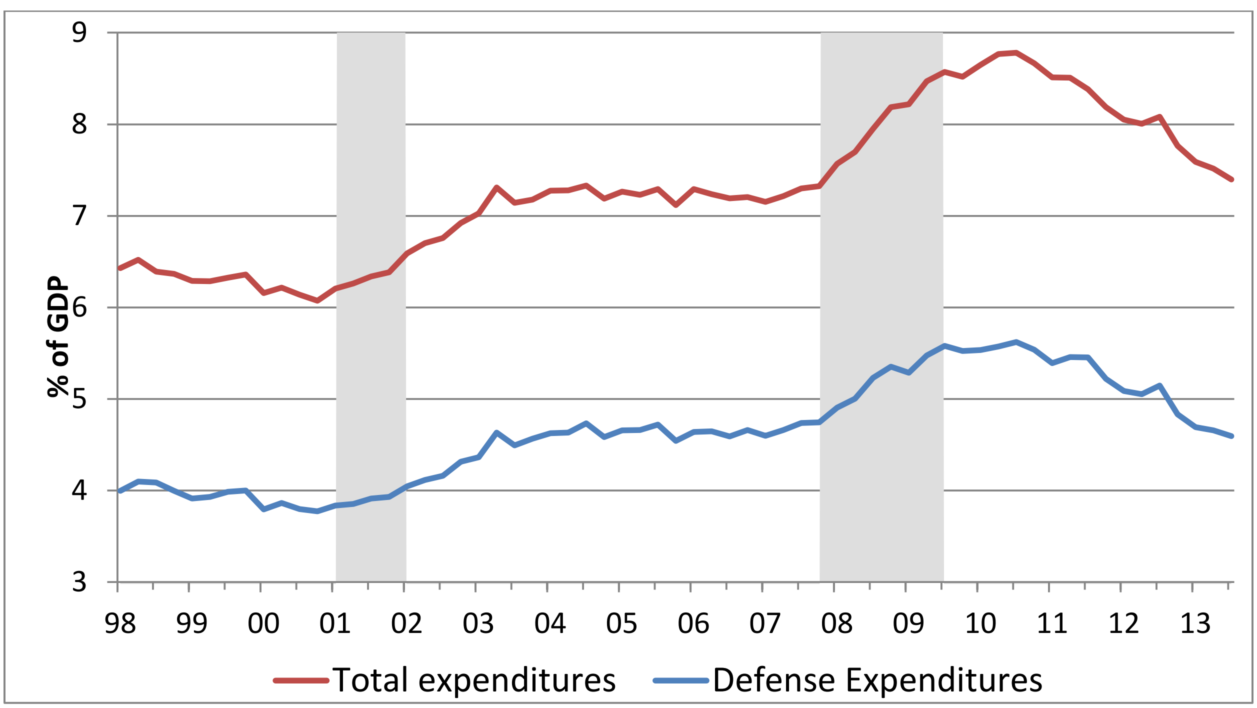
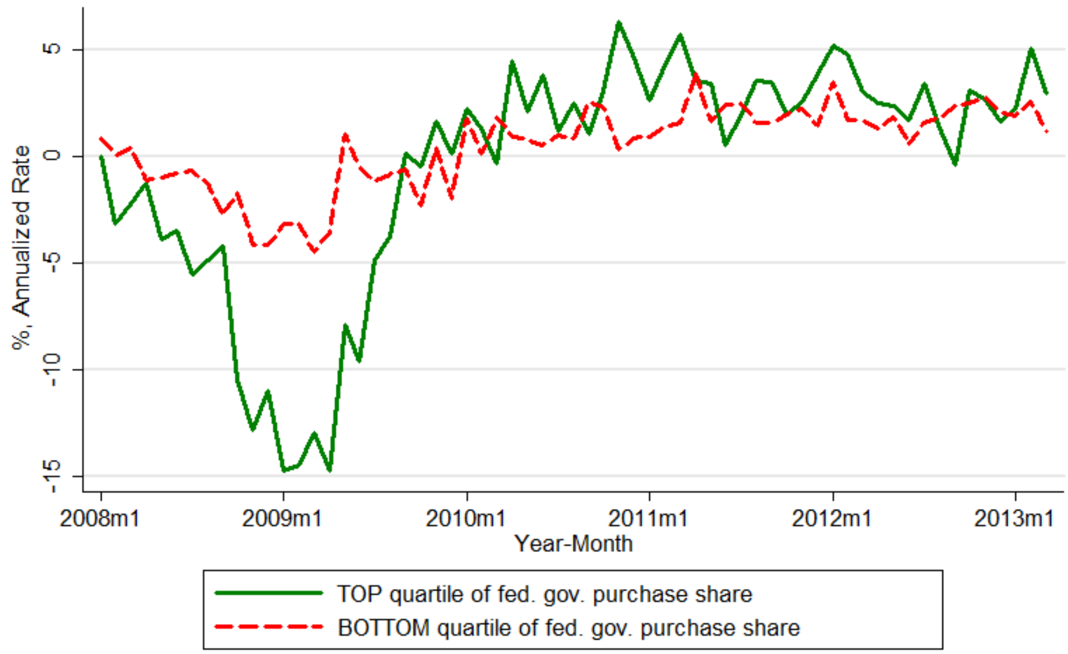
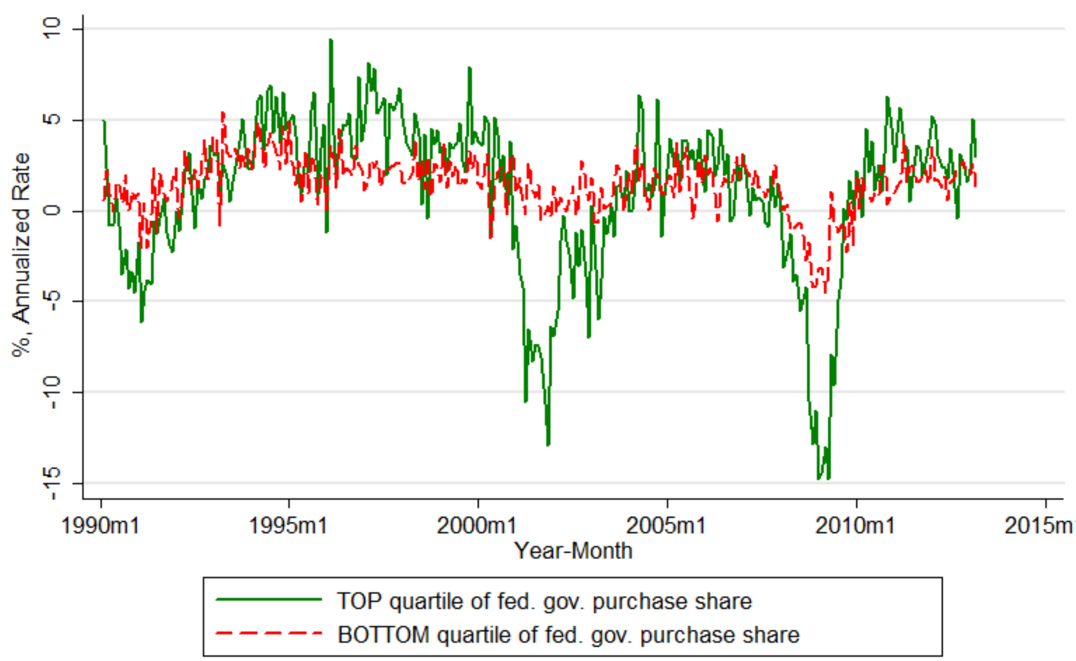


Figure 2a. Growth rate of *total* employees by industry group, Jan. 2008 to Mar. 2013



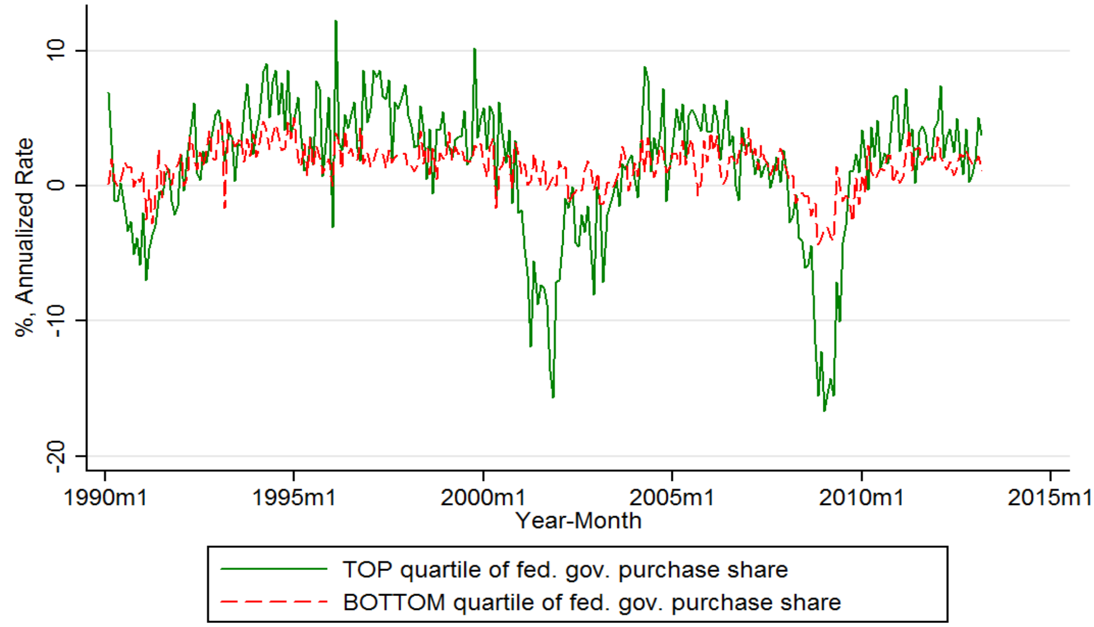
Source: Author's calculations.

Figure 2b. Growth rate of *total* employees by industry group, Feb. 1990 to Mar. 2013



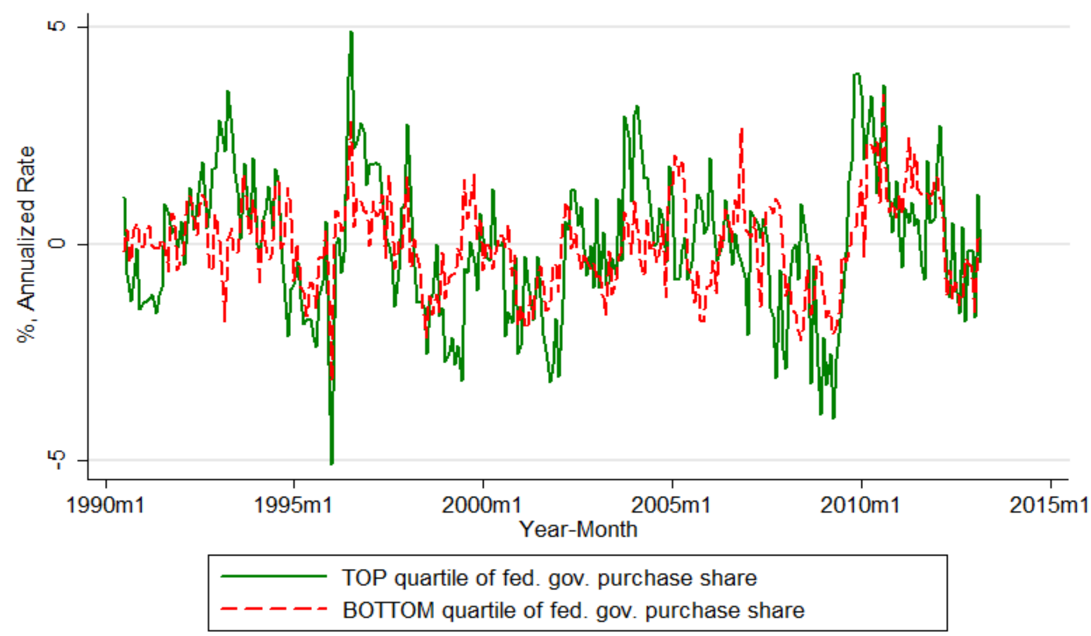
Note: These two charts compare the monthly growth of total employees on the payroll between the top and the bottom quartiles of industries using the 2002–2007 average shares of direct and indirect sales to the federal government.
Source: Author's calculations.

Figure 3. Growth rate of *production* employees by industry group, Feb. 1990 to Mar. 2013



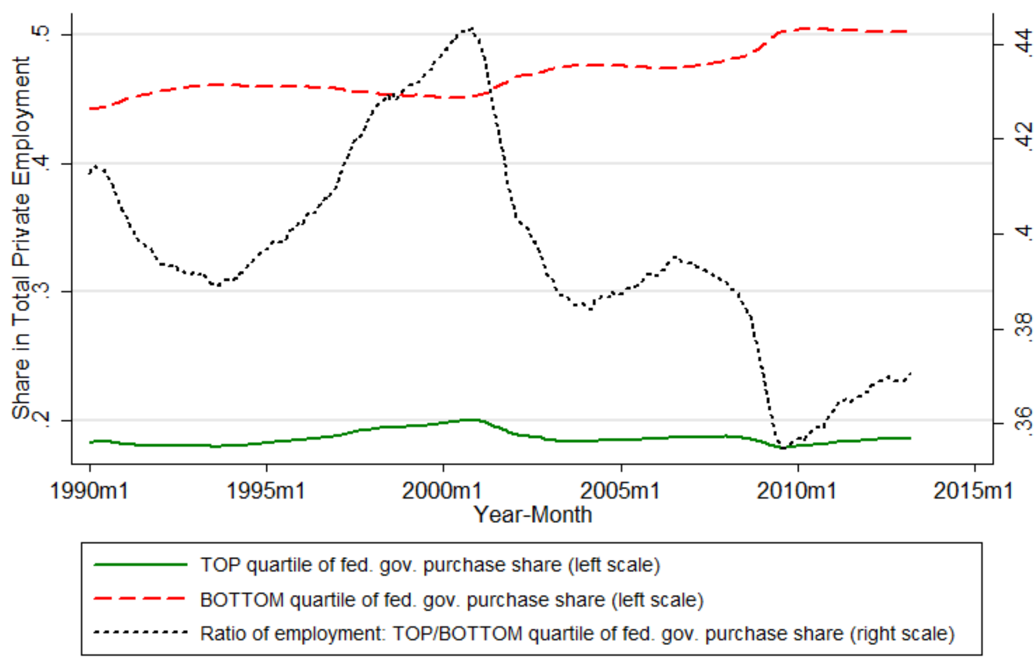
Note: This chart compares the monthly growth of production and nonsupervisory employees between the top and the bottom quartiles of industries using the 2002–2007 average shares of direct and indirect sales to the federal government.
Source: Author's calculations.

Figure 4. Growth rate of average weekly *hours* of production employees by industry group, Feb. 1990 to Mar. 2013



Note: This chart compares the 6-month trailing moving average of monthly growth of average weekly hours of production employees between the top and the bottom quartiles of industries using the 2002–2007 average shares of direct and indirect sales to the federal government.
Source: Author's calculations.

Figure 5. Share in total employees of private nonfarm industries by share of sales to the federal government



Source: Author's calculations.

Figure 6. Cyclicality of exports and federal defense spending

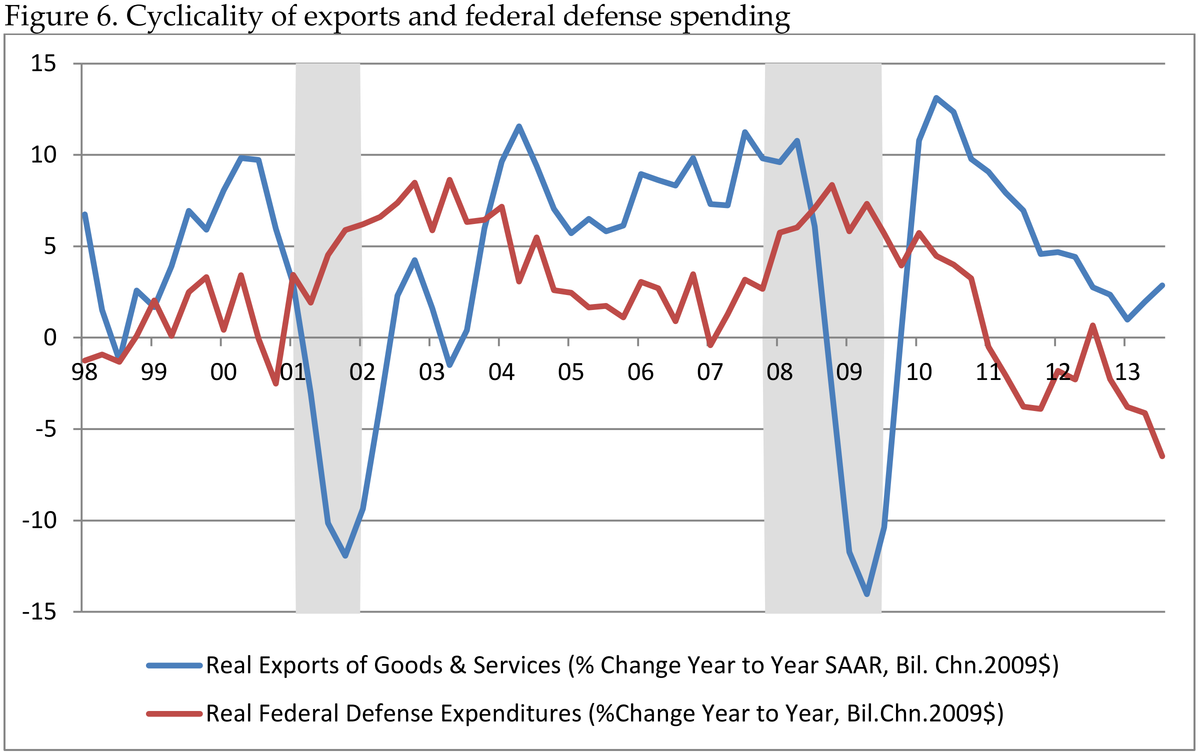
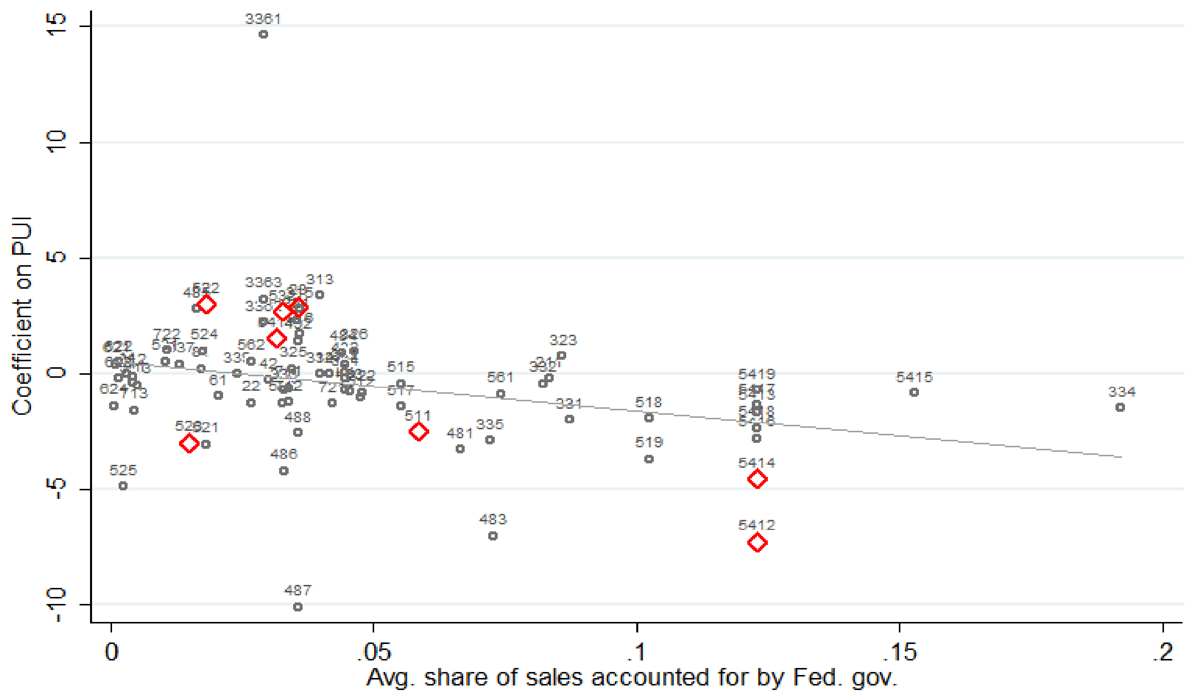
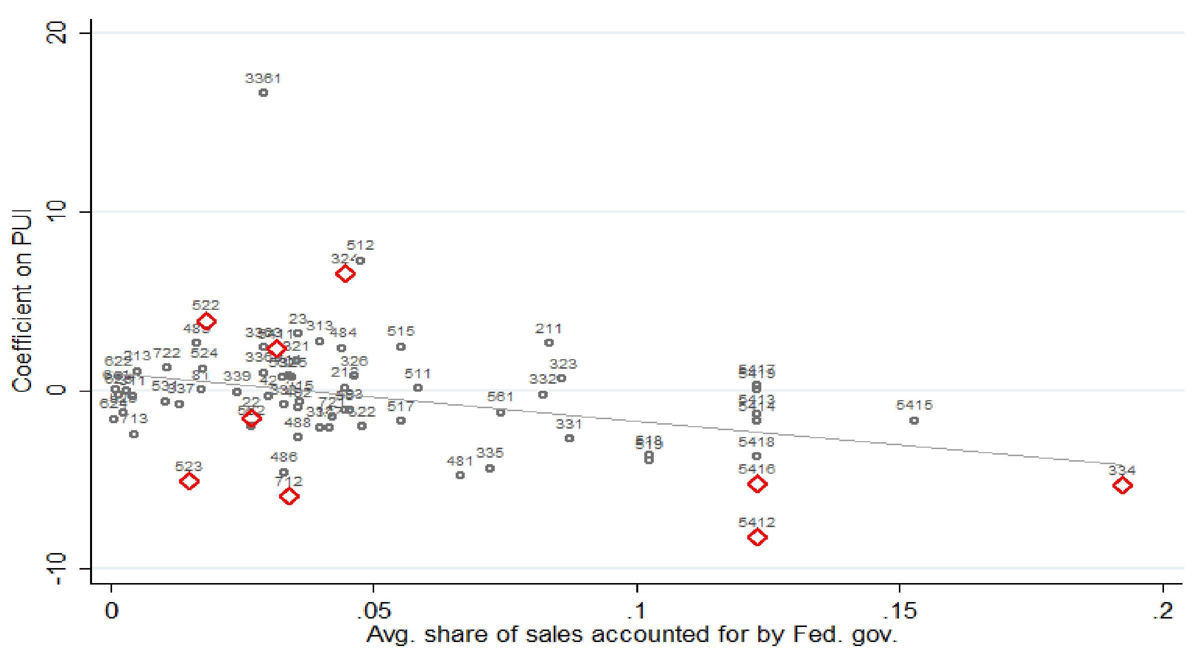


Figure 7. Relationship between industry (time-series) average share of sales accounted for by the federal government and industry-specific coefficient on PUI

Panel A: PUI estimates from the CCEMG total-employee regression (column (2) of Table 7)



Panel B: PUI estimates from the CCEMG production-employee regression (column (3) of Table 7)



Note: Significant *PUI* coefficients are marked in red.

Appendix A. Derivation of the Total Requirements Tables for Input-Output Analysis

This appendix briefly describes the derivation of the total requirements tables from the basic use and make input-output tables. The use table is essentially a commodity-by-industry matrix where the element (i, j) in row i and column j reports the amount of commodity i used by industry j in producing its output. The make table, on the other hand, is an industry-by-commodity matrix where the element (i, j) shows the amount of a given commodity j that is produced in industry i. The discussion here adapts the relevant materials from the technical note provided by the BEA along with the input-output data, which provides more details.[49]

Let q denote the $m\times 1$ vector of commodity output, and y the $n\times 1$ vector of industry gross output. Define B to be the direct input coefficients matrix in which entry (i, j) shows the amount of commodity i used by industry j per dollar of j's output. It is a $m\times n$, commodity-by-industry, matrix derived from the standard use table by normalizing each element (i, j) in the use table with industry j's total output, both measured in current dollars. Analogously, define D to be the market share (or transformation) matrix in which entry (i, j) measures the proportion of the total output of commodity i produced in industry j. So D is a $n\times m$ industry-by-commodity matrix. Let E denote the $m\times r$ matrix of final demand purchases of commodities; each entry (i, k) contains the value of commodity i supplied to final expenditures k, such as consumption, business investment and government spending. Then the $m\times 1$ vector of total final demand for commodities $e = E\iota$, where ι is a $r\times 1$ vector of 1's.

From the above definitions, total commodity output q and industry output y can be expressed as follows:

$$q = By + e \qquad \text{and} \qquad y = Dq\ . \tag{A.1}$$

Substituting the latter into the former and solving for q then yields:

$$q = (I - BD)^{-1}\, e. \tag{A.2}$$

I is a $m\times m$ identity matrix. The matrix $\boldsymbol{(I - BD)^{-1}}$ is known as the commodity-by-commodity ($m\times m$) total requirements matrix. It measures the total commodity output the economy produces in order to provide one dollar of each commodity to final users.

If we then substitute (A.2) into $y = Dq$, we have the following relationship between y and e:

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[49] The note can be downloaded at http://www.bea.gov/industry/zip/cxctr2002detail.zip. For more in-depth exposition of the input-output table, see Horowitz and Planting (2006).

$$y = D(I - BD)^{-1}\, e. \tag{A.3}$$

The matrix $D(\boldsymbol{I} - \boldsymbol{BD})^{-1}$ is known as the industry-by-commodity total requirements matrix. It shows the total amount of each commodity needed to be produced by each industry in order to supply one dollar of that commodity to final users. In the input-output analysis, it is assumed that each commodity is supplied in fixed proportion by each industry regardless of the exact final use. Under this assumption, the matrix $D(\boldsymbol{I} - \boldsymbol{BD})^{-1}$ then measures the industry-by-commodity total requirements for any individual final demand, be it consumption expenditures or government spending. Specifically, if we substitute the vector of final purchases by the federal government (for both defense and nondefense purposes), denoted g, for the total final demand e, $D(\boldsymbol{I} - \boldsymbol{BD})^{-1}g$ then yields the total industry output needed to satisfy federal government purchases.

Accordingly, we define an industry's government exposure as the share of the industry's output that eventually goes to satisfy federal government purchases in final expenditures. Denote it as s^G. It can be expressed as follows:

$$s^G = Y^{-1}\, D(I - BD)^{-1}\, g. \tag{A.3}$$

$\boldsymbol{Y}^{-1}$ denotes the $n \times n$ matrix whose the diagonal is formed by the inverse of each industry's total output. Analogously, we can define the share of an industry's output that goes to satisfy federal government final purchases for defense and nondefense purposes as $s^D = Y^{-1}\, D(I - BD)^{-1}\, g^D$ and $s^{ND} = Y^{-1}\, D(I - BD)^{-1}\, g^{ND}$, where g^D and g^{ND} denote the dollar value of defense and nondefense expenditures, respectively.

Likewise, we define an industry's exposure to exports as the share of the industry's output that eventually goes to satisfy exports in final expenditures. Denote it as s^{Exp}, and the vector of commodities going to satisfy exports as e^X. Then s^{Exp} can be expressed as follows, where :

$$s^{Exp} = Y^{-1}\, D(I - BD)^{-1}\, e^X. \tag{A.3}$$

We should also note that we are using the supplementary total requirements table after redefinition, although it makes essentially no quantitative difference for the regression analysis. We briefly describe the redefinition process below, which is a treatment necessitated by the reality that each industry typically produces multiple commodities (even at the relatively low level of disaggregation published in the input-output tables). So to attribute commodity input and output to industries, either the industry-technology assumption (ITA) or the commodity-technology assumption (CTA) has to be adopted. The ITA supposes that all commodities made by an industry share the same input structure. In contrast, the CTA proposes that each commodity has a unique input structure that is independent of the producing industry.

The BEA adopts a two-step hybrid approach that combines the ITA and the CTA in calculating the total requirements matrices. First, applying the CTA, the BEA moves each industry's secondary products, which are defined as those that require significantly different input structure than the industry's primary products, to an industry where they are primary. The associated inputs are also reallocated. These redefinitions and reallocations form the basis for the supplementary tables. From these tables, the ITA is then followed to derive the total requirements tables.

Table A.1. Industries Included in the Study

Descriptions	BEA Input-Output Codes	2002 NAICS codes
Mining	**21**	**21**
Oil and gas extraction	211	211
Mining, except oil and gas	212	212
Support activities for mining	213	213
Utilities	**22**	**22**
Construction	**23**	**23**
Manufacturing	**31G**	**31, 32, 33**
Durable goods	33DG	33, 321, 327
Wood products	321	321
Nonmetallic mineral products	327	327
Primary metals	331	331
Fabricated metal products	332	332
Machinery	333	333
Computer and electronic products	334	334
Electrical equipment, appliances, and components	335	335
Motor vehicles, bodies and trailers, and parts	3361MV	3361, 3362, 3363
Other transportation equipment	3364OT	3364, 3365, 3366, 3369
Furniture and related products	337	337
Miscellaneous manufacturing	339	339
Nondurable goods	31ND	31, 32 (except 321 and 327)
Food and beverage and tobacco products	311FT	311, 312
Textile mills and textile product mills	313TT	313, 314
Apparel and leather and allied products	315AL	315, 316
Paper products	322	322
Printing and related support activities	323	323
Petroleum and coal products	324	324
Chemical products	325	325
Plastics and rubber products	326	326
Wholesale trade	**42**	**42**
Retail trade	**44RT**	**44, 45**
Transportation and warehousing	**48TW**	**48, 49 (except 491)**
Air transportation	481	481
Rail transportation	482	482
Water transportation	483	483
Truck transportation	484	484
Transit and ground passenger transportation	485	485
Pipeline transportation	486	486
Other transportation and support activities	487OS	487, 488, 492
Warehousing and storage	493	493

Descriptions	BEA IO Codes	2002 NAICS codes
Information	**51**	**51**
Publishing industries (includes software)	511	511, 516
Motion picture and sound recording industries	512	512
Broadcasting and telecommunications	513	515, 517
Information and data processing services	514	518, 519
Finance, insurance, real estate, rental, and leasing	**FIRE**	**52, 53**
Finance and insurance	**52**	**52**
Federal Reserve banks, credit intermediation, and related activities	521CI	521, 522
Securities, commodity contracts, and investments	523	523
Insurance carriers and related activities	524	524
Funds, trusts, and other financial vehicles	525	525
Real estate and rental and leasing	**53**	**53**
Real estate	531	531
Rental and leasing services and lessors of intangible assets	532RL	532, 533
Professional and business services	**PROF**	**54, 55, 56**
Professional, scientific, and technical services	**54**	**54**
Legal services	5411	5411
Computer systems design and related services	5415	5415
Miscellaneous professional, scientific, and technical services	5412OP	5412-5414, 5416-5419
Management of companies and enterprises	**55**	**55**
Administrative and waste management services	**56**	**56**
Administrative and support services	561	561
Waste management and remediation services	562	562
Educational services, health care, and social assistance	**6**	**6**
Educational services	**61**	**61**
Health care and social assistance	**62**	**62**
Ambulatory health care services	621	621
Hospitals and nursing and residential care facilities	622HO	622, 623
Social assistance	624	624
Arts, entertainment, recreation, accommodation, and food services	**7**	**7**
Arts, entertainment, and recreation	**71**	**71**
Performing arts, spectator sports, museums, and related activities	711AS	711, 712
Amusements, gambling, and recreation industries	713	713
Accommodation and food services	**72**	**72**
Accommodation	721	721
Food services and drinking places	722	722
Other services, except government	**81**	**81**

Note: Data of three- and four-digit industries are used whenever available, and the corresponding two-digit level data are then excluded.

Appendix B. Summary Statistics and Additional Regression Results for Robustness Tests

Table B.1. Summary Statistics of the Variables Included in the Regressions

Variable	N	Mean	Standard Deviation	10th Percentile	50th Percentile	90th Percentile
Industry total employees	4697	-0.120	6.268	-7.338	0.562	6.020
Industry production employees	4209	-0.030	7.071	-8.373	0.625	7.364
Industry average weekly hours	4209	0.048	5.249	-5.480	0.000	5.701
Policy uncertainty index	4697	1.124	0.371	0.731	1.001	1.693
Share of industry output ultimately attributed to federal government purchases	4697	0.049	0.045	0.005	0.036	0.118
Share of industry output ultimately attributed to federal defense purchases	4697	0.032	0.030	0.003	0.024	0.076
Share of industry output ultimately attributed to federal nondefense purchases	4697	0.017	0.015	0.002	0.012	0.041
Share of industry output ultimately attributed to foreign purchases	4697	0.149	0.121	0.008	0.114	0.317
Real GDP	4697	2.062	3.628	-0.746	2.145	6.074
Federal government real defense spending	4697	2.461	32.181	-43.793	6.310	39.133
Real exports	4697	3.775	11.425	-7.499	5.911	15.667
Total employees on all private industry payroll	4697	0.527	2.383	-2.300	1.284	2.701
Production employees on all private industry payroll	4697	0.610	2.515	-2.365	1.440	2.692
Average weekly hours of production employees on all private industry payroll	4697	-0.153	1.240	-1.189	0.000	1.192
GI forecast of next 4-quarter GDP growth	4697	2.470	0.893	1.405	2.544	3.504
GI forecast of next 4-quarter growth in federal defense spending	4697	0.596	2.909	-3.858	0.825	3.962
GI forecast of next 4-quarter growth in federal nondefense spending	4697	1.785	2.940	-1.852	1.817	5.054

Table B.2. Common-correlated-effects (CCE) panel estimators for quarterly growth of employees and average weekly hours, with each industry weighted by its average number of employees over the sample period

VARIABLES	(1) Total Employees, All Industries	(2) Total Employees, Matched Sample	(3) Production Employees	(4) Average Weekly Hours
PUI	**0.221**	**0.260**	**0.283**	**0.225**
	[0.193]	**[0.197]**	**[0.242]**	**[0.247]**
High government purchase share * PUI	**-1.368*** **	**-1.359*** **	**-1.735*** **	**-0.438**
	[0.436]	**[0.439]**	**[0.604]**	**[0.354]**
Sum of lags of own growth (3 for employees, 1 for hours)	0.609***	0.617***	0.559***	-0.107
	[0.054]	[0.053]	[0.055]	[0.066]
Sum of Total private prod. employees or hours growth (t-3 to t for employees, t for hours)	0.341***	0.346***	0.398***	0.664***
	[0.059]	[0.060]	[0.076]	[0.103]
Sum of Durable dummy * Total empl. or hours growth (t-3 to t for employees, t for hours)	0.127***	0.117***	0.184***	0.944***
	[0.091]	[0.091]	[0.113]	[0.264]
Production employees growth (t)				0.0816**
				[0.0314]
GI forecast of fed. gov. defense spending growth over next 4 quarters * Government defense purchase share in output	-0.618	-0.531	-0.645	1.624***
	[0.857]	[0.845]	[0.892]	[0.576]
GI forecast of fed. gov. nondefense spending growth over next 4 quarters * Gov. nondefense purchase share in output	-4.363***	-4.269***	-5.652***	-1.546
	[1.041]	[1.050]	[1.550]	[1.454]
GI forecast of fed. gov. defense spending growth over next 4 quarters	-0.0187	-0.0217	-0.0226	0.00677
	[0.0284]	[0.0287]	[0.0339]	[0.0230]
GI forecast of fed. gov. nondefense spending growth over next 4 quarters	0.0853***	0.0905***	0.105***	-0.00888
	[0.0262]	[0.0267]	[0.0301]	[0.0333]
Government purchase share in output	8.192*	8.589*	9.981*	5.318*
	[4.407]	[4.609]	[5.965]	[2.902]
Constant	-0.135	-0.228	-0.182	-0.298
	[0.415]	[0.423]	[0.501]	[0.308]
Observations	4,697	4,209	4,209	4,209
R-squared	0.516	0.533	0.468	0.105
Adjusted R-squared	0.514	0.531	0.466	0.102
Number of NAICS code	77	69	69	69
Quarters per NAICS code	61	61	61	61

Notes: The same set of regression specifications as those underlying Table 6. All growth rates are annualized rate. Each column header denotes the dependent variable and the industries in the sample when relevant. Robust standard errors in brackets. *** p < 0.01, ** p < 0.05, * p < 0.1.
Source: Author's calculations.

Table B.3. Equal-weighted common-correlated-effects (CCE) panel estimators for quarterly growth of employees and average weekly hours: the aggregate controls equal to equal-weighted average of the dependent and the relevant independent variables

VARIABLES	(1) Total Employees, Total Industries	(2) Total Employees, Matched Sample	(3) Production Employees	(4) Average Weekly Hours
PUI	**0.387**	**0.444**	**0.628**	**0.166**
	[0.268]	**[0.271]**	**[0.397]**	**[0.338]**
High government purchase share * PUI	**-1.565*** **	**-1.806*** **	**-2.470*** **	**-0.135**
	[0.476]	**[0.426]**	**[0.553]**	**[0.533]**
Sum of lags of own growth (3 for employees, 1 for hours)	0.431***	0.519***	0.448***	-0.064
	[0.081]	[0.052]	[0.056]	[0.041]
Sum of Total private prod. employees or hours growth (t-3 to t for employees, t for hours)	0.510***	0.438***	0.501***	0.739***
	[0.091]	[0.067]	[0.077]	[0.112]
Sum of Durable dummy * Total empl. or hours growth (t-3 to t for employees, t for hours)	0.250***	0.208***	0.259***	1.514***
	[0.101]	[0.078]	[0.084]	[0.437]
Production employees growth (t)				0.0314
				[0.0234]
GI forecast of fed. gov. defense spending growth over next 4 quarters * Government defense purchase share in output	-1.201	-1.062	-0.520	1.362*
	[1.162]	[1.204]	[1.248]	[0.803]
GI forecast of fed. gov. nondefense spending growth over next 4 quarters * Gov. nondefense purchase share in output	-3.823	-3.580	-4.898*	0.489
	[2.325]	[2.216]	[2.713]	[1.651]
GI forecast of fed. gov. defense spending growth over next 4 quarters	0.0266	0.0283	0.0108	-0.0272
	[0.0533]	[0.0561]	[0.0646]	[0.0467]
GI forecast of fed. gov. nondefense spending growth over next 4 quarters	0.0635	0.0666	0.0920	-0.0139
	[0.0644]	[0.0595]	[0.0678]	[0.0494]
Government purchase share in output	-3.110	3.890	6.196	-0.00891
	[5.924]	[4.302]	[5.845]	[3.645]
Constant	0.200	-0.0885	-0.192	-0.132
	[0.433]	[0.377]	[0.564]	[0.399]
Observations	4,697	4,209	4,209	4,209
R-squared	0.329	0.421	0.356	0.088
Adjusted R-squared	0.326	0.418	0.352	0.0845
Number of NAICS code	77	69	69	69
Quarters per NAICS code	61	61	61	61

Notes: The same set of regression specifications as those underlying Table 6. All growth rates are annualized rate. Each column header denotes the dependent variable and the industries in the sample when relevant. Robust standard errors in brackets. *** p < 0.01, ** p < 0.05, * p < 0.1.

Source: Author's calculations.

Table B.4. Panel regression estimates for quarterly growth of employees and average weekly hours, with GDP growth as controls for macroeconomic conditions

VARIABLES	(1) Tot. employees, All Industries	(2) Total employees, Matched Sample	(3) Production Employees	(4) Average Weekly Hours
PUI	**-1.317*** **	**-1.222** **	**-1.079**	**-1.637*** **
	[0.464]	**[0.493]**	**[0.697]**	**[0.608]**
High government purchase share * PUI	**-1.588*** **	**-1.982*** **	**-2.715*** **	**-0.127**
	[0.537]	**[0.486]**	**[0.647]**	**[0.538]**
Sum of lags of own growth (3 for employees, 2 for hours)	0.440***	0.516***	0.453***	-0.067
	[0.074]	[0.049]	[0.054]	[0.042]
Sum of GDP growth (t-3 to t)	0.279***	0.274***	0.298***	0.198***
	[0.057]	[0.055]	[0.062]	[0.067]
Sum of Durable dummy * GDP growth (t-3 to t)	0.403***	0.332***	0.456***	0.011
	[0.114]	[0.092]	[0.118]	[0.090]
GI forecast of GDP growth over next 4 quarters	0.211	0.189	0.198	0.0664
	[0.164]	[0.168]	[0.198]	[0.144]
Durable*GI forecast of GDP growth over next 4 quarters	0.461**	0.509***	0.590**	0.256
	[0.182]	[0.192]	[0.242]	[0.190]
Production employees growth (t)				0.0382
				[0.0247]
GI forecast of fed. gov. defense growth over next 4 quarters * Gov. defense purchase share in output	-1.100	-1.153	-0.624	1.684**
	[1.186]	[1.174]	[1.272]	[0.809]
GI forecast of fed. gov. nondefense growth over next 4 quarters * Gov. nondefense purchase share in output	-3.735	-3.172	-4.154	0.0567
	[2.359]	[2.197]	[2.677]	[1.580]
GI forecast of fed. gov. defense spending growth over next 4 quarters	-0.132**	-0.112**	-0.156**	0.0691
	[0.0580]	[0.0543]	[0.0669]	[0.0456]
GI forecast of fed. gov. nondefense spending growth over next 4 quarters	0.0917	0.122*	0.0975	0.153**
	[0.0676]	[0.0662]	[0.0710]	[0.0658]
Government purchase share in output	0.950	10.73	16.52*	3.538
	[8.349]	[7.096]	[9.164]	[2.842]
2001 recession dummy	-2.302***	-1.895***	-2.259***	0.522
	[0.533]	[0.393]	[0.480]	[0.393]
2008-9 recession dummy	-0.941	-0.852	-1.438*	1.152**
	[0.735]	[0.645]	[0.774]	[0.550]
Post-2009 recovery dummy	1.811**	2.063***	1.702*	3.491***
	[0.722]	[0.694]	[0.859]	[0.706]
Constant	0.314	-0.230	-0.381	-0.247
	[0.667]	[0.567]	[0.766]	[0.528]
Observations	4,697	4,209	4,209	4,209
R-squared	0.303	0.389	0.318	0.051
Adjusted R-squared	0.299	0.385	0.314	0.045
Number of NAICS code	77	69	69	69
Quarters per NAICS code	61	61	61	61

Notes: The same as for Table 6.
Source: Author's calculations.

Table B.5. Common-correlated-effects panel estimators for quarterly growth of employees and average weekly hours (the corresponding aggregate indicators as controls for unobserved general factors), with two lags of *PUI*

VARIABLES	(1) Total Employees, All Industries	(2) Tot. Employees, Matched Sample	(3) Production Employees	(4) Average Weekly Hours
Sum of PUI (t-2 to t)	**-0.299**	**-0.050**	**0.145**	**0.762****
	[0.276]	**[0.244]**	**[0.344]**	**[0.370]**
Sum of high government purchase share * PUI	**-1.895*****	**-2.250*****	**-3.286*****	**-0.472**
	[0.562]	**[0.499]**	**[0.701]**	**[0.652]**
Sum of lags of own growth (3 for employees, 2 for hours)	0.429***	0.513***	0.436***	-0.0530
	[0.082]	[0.052]	[0.058]	[0.041]
Sum of Total private prod. employees or hours growth (t-3 to t)	0.449***	0.398***	0.519***	0.498***
	[0.075]	[0.059]	[0.075]	[0.107]
Sum of Durable dummy * Total empl. or hours growth (t-3 to t)	0.218***	0.127***	0.213***	1.181***
	[0.116]	[0.092]	[0.106]	[0.340]
Production employees growth (t)				0.0361
				[0.0250]
GI forecast of fed. gov. defense spending growth over next 4 quarters * Government defense purchase share in output	-1.653	-1.736	-1.673	1.259
	[1.163]	[1.210]	[1.307]	[0.873]
GI forecast of fed. gov. nondefense spending growth over next 4 quarters * Gov. nondefense purchase share in output	-3.108	-2.691	-3.534	0.0674
	[2.252]	[2.151]	[2.629]	[1.585]
GI forecast of fed. gov. defense spending growth over next 4 quarters	-0.0559	-0.0417	-0.0303	0.0458
	[0.0535]	[0.0545]	[0.0620]	[0.0393]
GI forecast of fed. gov. nondefense spending growth over next 4 quarters	0.0210	0.0236	0.0394	-0.0600
	[0.0657]	[0.0642]	[0.0721]	[0.0447]
Government purchase share in output	-1.065	6.899	9.630*	1.109
	[6.521]	[4.677]	[5.766]	[3.074]
Constant	0.965*	0.478	0.312	-0.553
	[0.497]	[0.390]	[0.560]	[0.424]
Observations	4,697	4,209	4,209	4,209
R-squared	0.318	0.406	0.341	0.055
Adjusted R-squared	0.314	0.403	0.337	0.0506
Number of NAICS code	77	69	69	69
Quarters per NAICS code	61	61	61	61

Notes: All growth rates are annualized rate. Each column header denotes the dependent variable and the industries in the sample when relevant. Robust standard errors in brackets. *** p < 0.01, ** p < 0.05, * p < 0.1.
Source: Author's calculations.

Table B.6. Panel regression estimates for quarterly growth of employees and average weekly hours, with GDP growth as controls for macroeconomic conditions

VARIABLES	(1) Total Employees, All Industries	(2) Tot. Empl., Matched Sample	(3) Production Employees	(4) Average Weekly Hours
Sum of PUI (t-2 to t)	**-2.360*** **	**-2.076*** **	**-2.571*** **	**-1.905*** **
	[0.578]	**[0.591]**	**[0.792]**	**[0.688]**
Sum of high government purchase share * PUI	**-1.824*** **	**-2.299*** **	**-3.380*** **	**-0.507**
	[0.625]	**[0.570]**	**[0.788]**	**[0.673]**
Sum of lags of own growth (3 for employees, 2 for hours)	0.437***	0.513***	0.448***	-0.0670
	[0.074]	[0.049]	[0.054]	[0.041]
Sum of GDP growth (t-3 to t)	0.248***	0.244***	0.259***	0.213***
	[0.055]	[0.053]	[0.063]	[0.067]
Sum of Durable dummy * GDP growth (t-3 to t)	0.405***	0.335***	0.463***	0.016
	[0.115]	[0.093]	[0.120]	[0.089]
GI forecast of GDP growth over next 4 quarters	0.368**	0.319*	0.436**	0.124
	[0.176]	[0.177]	[0.210]	[0.160]
Durable*GI forecast of GDP growth over next 4 quarters	0.463**	0.512***	0.598**	0.263
	[0.181]	[0.191]	[0.242]	[0.191]
Production employees growth (t)				0.038
				[0.032]
GI forecast of fed. gov. defense growth over next 4 quarters * Gov. defense purchase share in output	-1.366	-1.495	-1.270	1.375
	[1.205]	[1.190]	[1.310]	[0.885]
GI forecast of fed. gov. nondefense growth over next 4 quarters * Gov. nondefense purchase share in output	-3.810	-3.160	-4.082	0.251
	[2.342]	[2.204]	[2.672]	[1.594]
GI forecast of fed. gov. defense spending growth over next 4 quarters	-0.154***	-0.126**	-0.181***	0.0647
	[0.0569]	[0.0533]	[0.0663]	[0.0446]
GI forecast of fed. gov. nondefense spending growth over next 4 quarters	0.101	0.124*	0.116*	0.177**
	[0.0638]	[0.0630]	[0.0693]	[0.0685]
Government purchase share in output	0.588	10.72	17.11*	4.848*
	[8.485]	[7.281]	[9.271]	[2.816]
2001 recession dummy	-2.207***	-1.823***	-2.097***	0.600
	[0.524]	[0.394]	[0.477]	[0.400]
2008-9 recession dummy	-0.452	-0.440	-0.695	1.322**
	[0.761]	[0.668]	[0.796]	[0.563]
Post-2009 recovery dummy	2.510***	2.642***	2.779***	3.798***
	[0.736]	[0.722]	[0.898]	[0.777]
Constant	1.106	0.477	0.724	-0.231
	[0.702]	[0.606]	[0.824]	[0.525]
Observations	4,697	4,209	4,209	4,209
R-squared	0.306	0.392	0.324	0.052
Adjusted R-squared	0.301	0.387	0.319	0.0453
Number of NAICS code	77	69	69	69
Quarters per NAICS code	61	61	61	61

Notes: The same as for Table B.5.

Table B.7. Panel regression estimates for quarterly growth of production employees and average weekly hours, IP industries only to control for industry own output growth

VARIABLES	(1) Prod. Employees, No Output	(2) Production Employees	(3) Avg. Weekly Hours, No Output	(4) Average Weekly Hours
PUI	**-2.798****	**-1.499****	**-2.494***	**-1.817***
	[1.073]	**[0.687]**	**[1.318]**	**[0.912]**
High government purchase share * PUI	**-1.632***	**-1.753***	**-0.532**	**-0.509**
	[0.898]	**[1.005]**	**[0.559]**	**[0.400]**
Output growth (t) * PUI		**0.0184**		**0.0540****
		[0.0377]		**[0.0251]**
Output growth (t) * PUI * High gov. purchase share		**-0.0257**		**-0.0274**
		[0.0186]		**[0.0226]**
Sum of output growth (GDP: t-3 to t; industry own: t-6 to t)	0.346***	0.429***	0.112	-0.006
	[0.148]	[0.084]	[0.119]	[0.058]
Sum of Durable dummy * GDP growth (t-3 to t)	0.514***		0.097	
	[0.156]		[0.074]	
Log(output) - log(employment) (t-1)		5.690***		
		[1.791]		
Production employee growth (t)			0.019	-0.0128
			[0.029]	[0.0794]
GI forecast of fed. gov. defense growth over next 4 quarters * Gov. defense purchase share in output	2.192	1.109	2.567**	1.744
	[1.403]	[0.935]	[1.018]	[1.003]
GI forecast of fed. gov. nondefense growth over next 4 quarters * Gov. nondefense purchase share in output	-4.109	-5.631	-1.680	-3.297
	[5.280]	[3.824]	[2.612]	[2.655]
GI forecast of fed. gov. defense spending growth over next 4 quarters	-0.200**	-0.349***	0.0687	0.0959
	[0.0819]	[0.0981]	[0.0690]	[0.0873]
GI forecast of fed. gov. nondefense spending growth over next 4 quarters	0.176	-0.0130	0.137	0.123
	[0.138]	[0.109]	[0.113]	[0.120]
Government purchase share in output	20.57**	-2.535	9.710*	6.182
	[7.975]	[19.36]	[4.875]	[4.875]
2001 recession dummy	-3.028***	-3.814***	1.165	0.168
	[0.646]	[0.723]	[0.687]	[0.595]
2008-9 recession dummy	0.251	-0.667	0.850	0.367
	[1.128]	[0.707]	[0.871]	[0.677]
Post-2009 recovery dummy	4.999***	0.619	4.655***	3.155***
	[1.621]	[0.806]	[1.319]	[0.819]
Constant	-3.298***	0.585	0.140	0.889
	[0.917]	[1.336]	[0.855]	[0.661]
Observations	1,098	1,098	1,098	1,098
R-squared	0.498	0.552	0.179	0.243
Adjusted R-squared	0.486	0.544	0.157	0.229
Number of NAICS code	18	18	18	18
Quarters per NAICS code	61	61	61	61

Notes: All growth rates are annualized rate. Each column header denotes the dependent variable and output control used. Robust standard errors in brackets. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.