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Measures of per Capita Hours and Their Implications for the Technology-Hours Debate

Structural vector autoregressions give conflicting results on the effects of technology shocks on hours. The results depend crucially on the assumed data generating process for hours per capita. We show that the standard measure of hours per capita and productivity have significant low-frequency movements that are the source of the conflicting results. Hodrick–Prescott (HP)-filtered hours per capita produce results consistent with those obtained when hours are assumed to have a unit root. We show that important sources of the low-frequency movements in the standard measure are sectoral shifts in hours and the changing age composition of the working-age population. When we control for these low-frequency components to determine the effect of technology shocks on hours using long-run restrictions we get one consistent answer: hours decline in the short run in response to a positive technology shock. We further extend the analysis by examining the effects of demographic controls on the impulse responses to investment-specific technology shocks. Our results are less conclusive.

JEL codes: E2, E3, J1
Keywords: business cycles, technology shocks, demographic shifts.

THE ROLE OF TECHNOLOGY SHOCKS in business cycle fluctuations has recently received considerable attention. A myriad of papers has emerged on this topic addressing the controversial conclusion reached by Galí (1999) that *technology shocks cannot be the main driving force behind cyclical movements in macroeconomic*

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data. This conclusion challenges the core of the long-standing real business cycle (hereafter, RBC) theory; thus, it comes as no surprise that so many recent papers have been written either in defense of or to challenge Galí's findings (see Galí and Rabanal 2004 for a review of the literature, Basu, Fernald, and Kimball 2006 for an alternative approach that yields similar findings, and Fisher 2006 who proposes an alternate technology shock that produces results consistent with the traditional RBC paradigm).

Standard RBC theory teaches that all factor inputs should rise when there is a positive technological innovation. However, recent empirical tests of the theory find that labor input falls in response to a positive shock to technology, a finding that has sparked a debate for the last decade with little resolution. The crux of the debate has to do with the data-generating process assumed for per capita labor input in empirical models. If one were to rely on econometrics, which fails to reject the presence of a unit root in per capita labor, one would be led to enter labor input in first differences when estimating a (structural) vector autoregression (VAR). Entered in differences the results of a typical VAR predict a fall in labor input in response to a positive shock to technology, opposite of that predicted by the standard RBC model. However, *common sense* tells us that per capita labor being a bounded series cannot have a unit root. For this reason, several papers have assumed per capita labor is stationary and, thus, should enter the VARs in levels. When entered in levels the standard result emerges that labor input rises when there is a positive innovation to technology.

In this paper, we show that there are significant low-frequency demographic and sectoral movements, over the postwar period, that are features of the commonly used measure of hours worked per capita as well as the growth rate of labor productivity. Our premise is that these low-frequency movements have nothing to do with the kinds of *technology shocks* typically modeled in RBC theory. These low-frequency movements in the standard measures distort unit root tests (which have low power to begin with), make the time series for per capita labor inconsistent over time and with RBC theory, and are the source of conflicting results in the levels versus first difference debate. Previous researchers, such as Flaim (1990), Shimer (1998), and Aaronson et al. (2006), have highlighted the effects of demographics on trends in aggregate series. None, however, has shown that demographic influences can seriously affect the results of structural VARs.

We begin by showing that extraction of these low-frequency movements from hours alone using a conservative Hodrick–Prescott (HP) filter produces results similar to those obtained using first-differenced hours. We then show that an important source of the low-frequency movements in both hours and productivity growth is the movement of the baby boom generation through the labor market. We also show that sectoral changes involving government and nonprofit employment induce trends in the standard measure of hours per capita, which counts only hours worked in private business. We demonstrate these points both empirically and theoretically. Ngai and Pissarides (2008) offer a model that generates a U-shape in market hours based on total factor productivity (TFP) growth across sectors and home production. We show most of the

U-shape in the data is simply due to demographics and incomplete counting of market hours.

Once we account for demographics and sectoral shifts, we show consistent implications for the role of technology shocks in business cycle fluctuations. Positive technology shocks, identified with long-run restrictions, lead to a short-run decrease in hours worked regardless of the stationary assumption made for per capita labor. On the other hand, the results are mixed for investment-specific technology shocks. In some specifications, positive investment-specific shocks raise hours while they lower productivity. In the specification that controls for demographics in a less structured way, positive investment-specific shocks raise productivity and lower hours. All specifications, however, have the common feature that hours move in the opposite direction of productivity.

Our results also have broader implications beyond the technology-hours debate. For example, our analysis of institutional and demographic changes explains the findings of Kahn and Rich (2007) and Fernández-Villaverde and Rubio-Ramírez (2007). Kahn and Rich use a regime-switching dynamic factor model to detect breaks in trend productivity growth. They show that there are two important sources of low-frequency movements in per capita macroeconomic variables: technology and slow movements in labor supply that look like preference shifts. Similarly, Fernandez-Villaverde and Rubio-Ramirez estimate a dynamic stochastic general equilibrium (DSGE) model and find that low-frequency movements in the preference parameter are an important part of fluctuations. Our results suggest that the sources of these movements are demographic changes in the "representative household" and institutional changes in the sectors of employment.

1. THE PROBLEM OF LOW-FREQUENCY MOVEMENTS IN HOURS PER CAPITA

According to RBC models with standard preference specifications, the hours worked per capita variable should be stationary in the absence of permanent shifts in government spending, labor income taxes, and preference shifts. Yet the most widely used measure of private hours per capita shows significant low-frequency movements. Figure 1 shows the behavior of private hours in business divided by the civilian noninstitutional population ages 16 and over during the post-WWII period. Hours show a U-shape, with a downward trend until the mid 1970s, which partially reverses by 1997, but then falls again afterward. The peak in 1979 is 14% below the peak in 1948. The low-frequency movements are so pronounced that the series does not return to its mean for decades at a time.

While these low-frequency features are not an issue for analyses that HP filter data before analyzing it, they are very problematic for structural VARs (SVARs) in which assumptions about stationarity are key parts of the identification. In particular, these low-frequency movements in hours per capita have important implications for

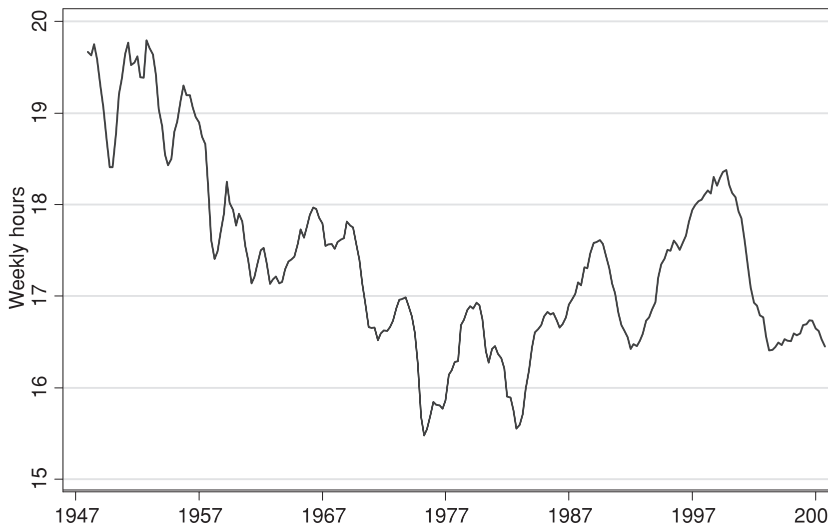


FIG. 1. Private Business Hours per Capita (Based on Civilian Noninstitutional Population Ages 16 and Over).

empirical structural VAR models that identify technology shocks using long-run restrictions. Based on the results of standard unit root tests, Francis and Ramey (2005) assume that hours per capita have a unit root, and thus enter hours in first differences in the model. They find that a positive technology shock leads to a decline in hours worked. In contrast, Christiano, Eichenbaum, and Vigfusson (CEV, 2003) argue that hours per capita cannot logically have a unit root, and offer alternative empirical tests against a unit root. They enter hours in levels and find that a positive technology shock leads to a rise in hours worked.[1]

To illustrate, we reestimate the structural VAR used by Galí (1999) and Ramey (2005), and CEV using the standard measure of hours. In the baseline bivariate case, we estimate the following system

$$\begin{bmatrix} \Delta x_t \\ n_t \end{bmatrix} = \begin{bmatrix} C^{11}(L) & C^{12}(L) \\ C^{21}(L) & C^{22}(L) \end{bmatrix} \begin{bmatrix} \varepsilon_t^z \\ \varepsilon_t^m \end{bmatrix},$$

where x_t denotes the log of labor productivity in private business, n_t denotes the log of hours per capita (measured as the ratio of hours in private business to the noninstitutional population aged 16 and over), ε^z denotes the technology shock, and ε^m denotes

1. This literature has generated a further controversy about whether these VARs can capture the results from the model. In particular, Chari, Kehoe, and McGrattan (2008) show that they can generate data from a model in which technology shocks have a positive effect on hours yet the VAR shows them to have negative effects. Christiano, Eichenbaum, and Vigfusson (2006), however, show that the Chari, Kehoe, McGrattan example is an anomaly, being at odds with the data. Erceg, Guerreri, and Gust (2005) and Francis, Owyang, and Roush (FOR, 2005) also show that VARs applied to artificial data from RBC models are consistent with the simulated results of the underlying model.

the nontechnology shock. $C(L)$ is a polynomial in the lag operator. We maintain the usual assumption that ε^z and ε^m are orthogonal. Our assumption identifying the technology shock implies that $C^{12}(1) = 0$, which restricts the unit root in productivity to originate solely in the technology shock.

This system applies to the case in which hours are assumed to be stationary. We also estimate a system in which hours are assumed to have a unit root

$$\begin{bmatrix} \Delta x_t \\ \Delta n_t \end{bmatrix} = \begin{bmatrix} C^{11}(L) & C^{12}(L) \\ C^{21}(L) & C^{22}(L) \end{bmatrix} \begin{bmatrix} \varepsilon_t^z \\ \varepsilon_t^m \end{bmatrix}.$$

We impose the same restriction, that $C^{12}(1) = 0$, to identify the technology shock. *It is important to note that one can identify the technology shock whether hours are stationary or nonstationary.* However, that identification of the technology shock is sensitive to the correct specification of hours, as we shall see below.

In the baseline case, we use four lags and limit our attention to a bivariate system. The data are quarterly and extend from 1948:1 through 2007:4. The standard error bands are 95% confidence bands based on bootstrap standard errors with 2,000 replications.

Recall the previous summary of the literature. Using standard measures of hours per capita, the specification with stationary hours implies that hours increase significantly in response to a technology shock. In contrast, the specification with a unit root in hours implies that hours fall significantly in response to a technology shock. This pattern can be seen in Figure 2 where we use the standard measure of hours per capita with the civilian population 16 and over as the population measure. The first column shows the results from the system with hours per capita in levels and the second column shows the results from the system estimated with hours per capita in first differences. The model is bivariate in the logs of labor productivity and hours, but we also show the implied effects for the log of output, since it is equal to the sum of the other two variables. The graphs display the same conflicting results from the literature.

Is the overdifferencing of hours per capita leading to erroneous results or are the low-frequency movements in the level of hours per capita leading to misleading results in the levels specification? To investigate the plausibility of these explanations, we remove the very low-frequency movements in hours per capita using a very conservative HP filter with a λ parameter set equal to 16,000 rather than the usual 1,600 for quarterly data. Figure 3 shows the estimated trend. It displays a pronounced U-shape, with the highest part in the early part of the sample. We then use the detrended hours series in the bivariate SVAR model, both in levels and first differenced.

Figure 4 shows the estimated impulse response functions using HP-filtered hours per capita, with the results from the levels specification on the left and the results from the first-differenced specification on the right. Interestingly, both specifications imply that a positive technology shock leads to a decline in hours in the short run, consistent with Galí's (1999) finding and Francis and Ramey's (2005) finding. Although one

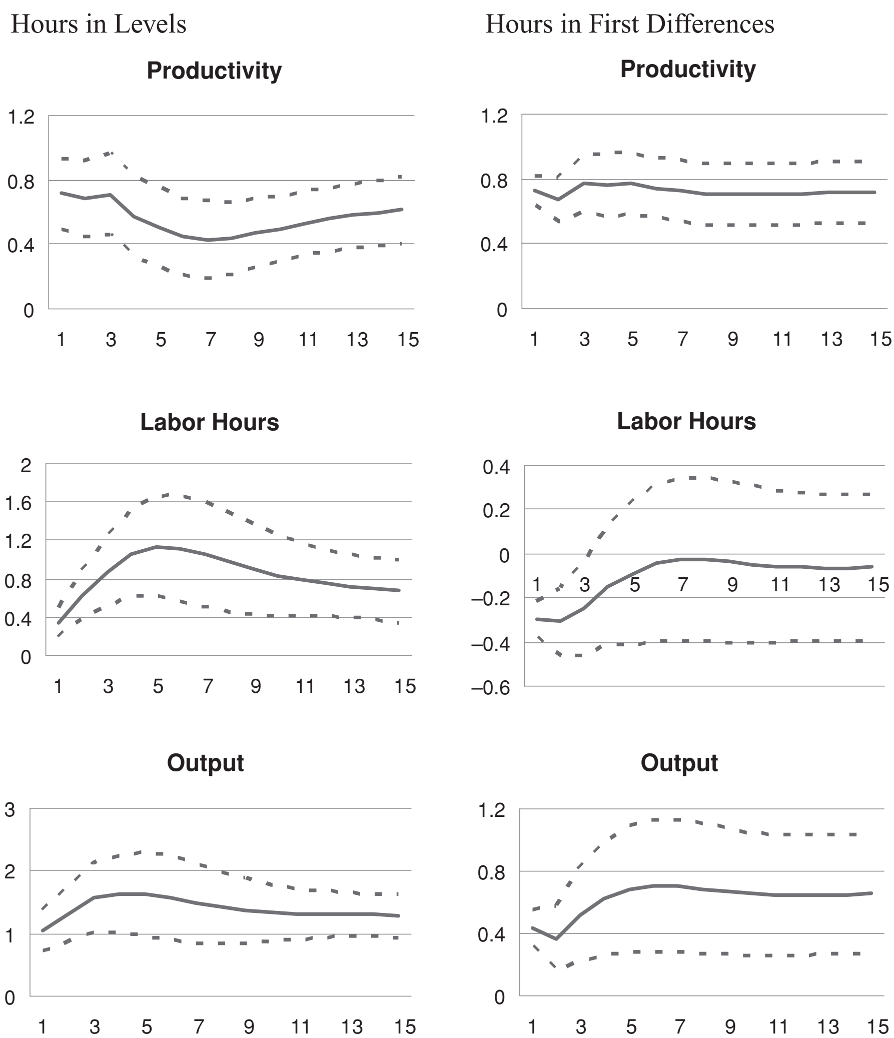


Fig. 2. Impulse Responses to a Technology Shock: Quarterly 1948–2007 (Business Hours/Civilian Population 16+, 95% Standard Error Bands).

would suppose that the difference specification is plagued by overdifferencing when HP-filtered hours are used, the results are quite similar to those when the filtered hours levels are used.[2]

These results support Fernald's (2007) contention that the coincidental U-shape in both productivity growth and the standard measure of hours per capita is driving

2. The results are similar when an HP filter with standard parameter values is used.

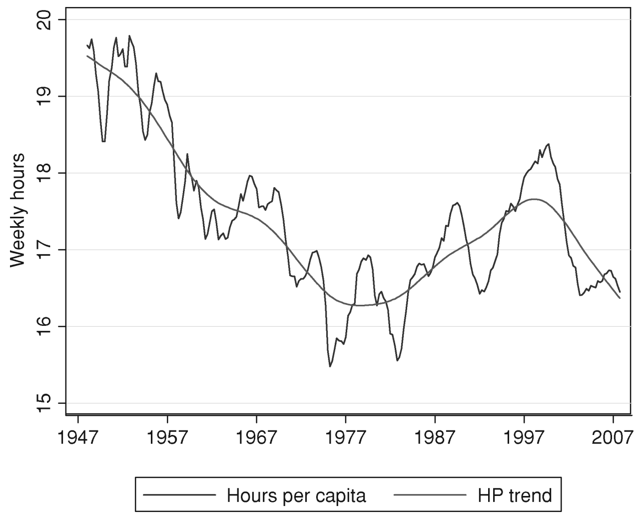


FIG. 3. Plot of Private Business Hours per Capita and Its HP-Filtered Trend ($\lambda = 16{,}000$).

CEV's finding of a positive response of hours. When Fernald removes the U-shape in productivity growth, but leaves the U-shape in the standard measure of hours per capita, he finds a negative effect of technology shocks on hours. Conversely, when we eliminate the U-shape in hours per capita by removing the low-frequency component, but do not allow for structural breaks in labor productivity, we also obtain the same negative response.[3]

In fact, we will show that the U-shapes in hours per capita and productivity growth are not necessarily coincidental. In particular, we will demonstrate both theoretically and empirically that the entry of the baby boom generation into the labor market led both hours per capita and labor productivity growth to be lower during the 1970s and 1980s. Our theory shows that the Galí (1999) identifying assumption for technology shocks is violated if there are low-frequency movements in the composition of the workforce. Moreover, we show that shifts in employment from private business to government and nonprofit induced further low-frequency movements in hours per capita.

2. PRIVATE BUSINESS HOURS VERSUS AGGREGATE HOURS

Many researchers have used private business hours per capita or nonfarm business hours as their hours measure, and then appealed to the standard assumption that

3. In a similar vein, both CEV (2003) and Francis and Ramey (2005) show that removing a quadratic trend from hours also leads to negative response of hours.

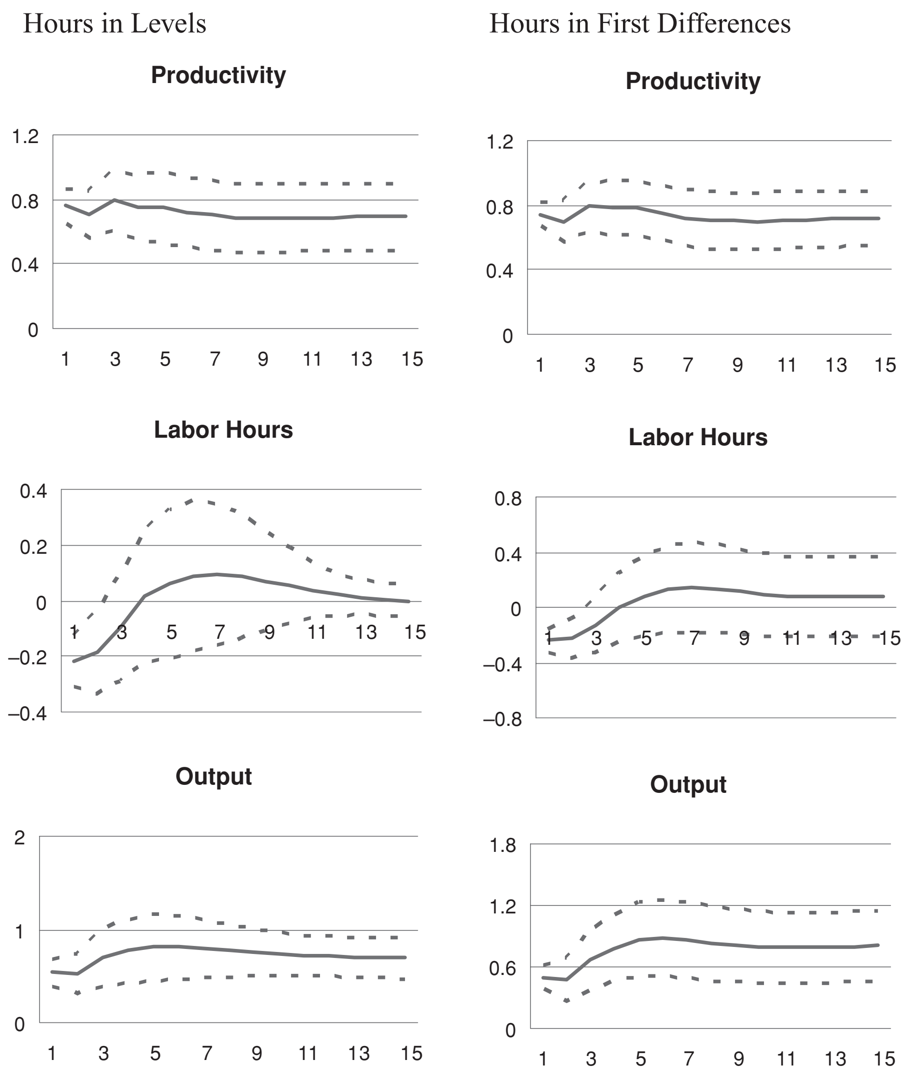


FIG. 4. Impulse Responses to a Technology Shock: Quarterly 1948–2007 (HP-Filtered Hours/Civilian Population 16+, 95% Error Bands).

income and substitution effects cancel to argue that this measure should be without trend (e.g., CEV 2003). However, the argument on income and substitution effects applies to aggregate hours (or leisure), not necessarily to hours worked in one sector. If there is a trend in the share of hours worked in the private business sector, then this measure of hours per capita will have a trend even when aggregate hours per capita have no trend.

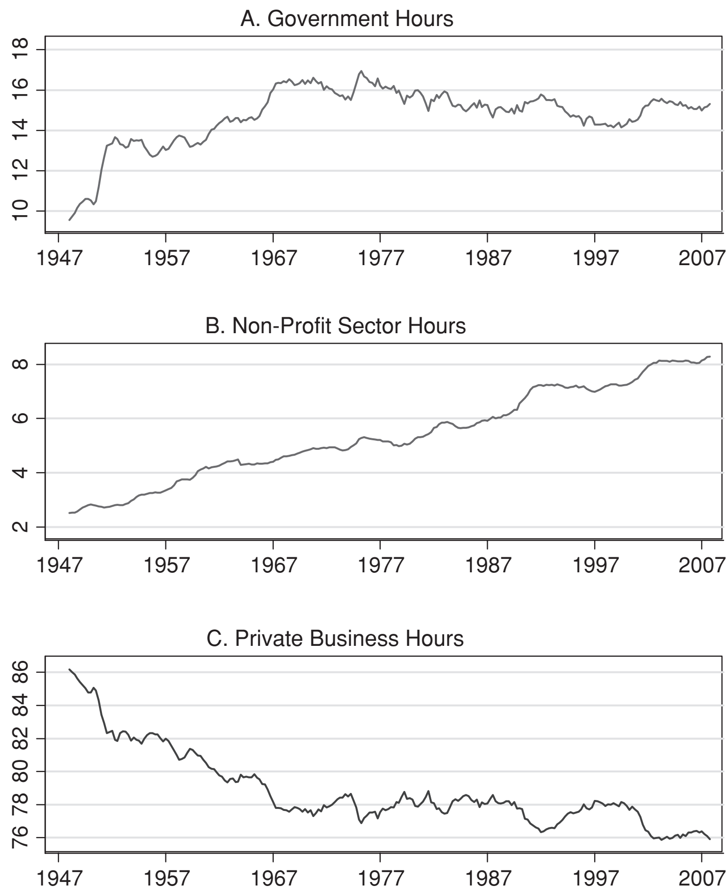


FIG. 5. Hours Worked by Sector (Percentage of Total).

Private business hours is the most aggregated hours series published by the Bureau of Labor Statistics (BLS) as part of its productivity and cost program, but it is a decreasing fraction of all hours worked. To demonstrate this, we obtained unpublished quarterly data from the BLS on all sectors of the economy from 1948 to 2007. Figure 5A shows the behavior of hours worked in government as a fraction of total hours worked in private business, government, the nonprofit sector, and private households.[4] Government hours rise from below 10% in 1948 to over 17% in the late 1970s and then fluctuate between 15% and 16% for the last 30 years. Note that the increase in government hours as a percentage of total hours worked from 1948 to the 1970s mirrors the decline in private business hours per capita shown in Figure 1.

4. Hours worked in private households are very small. They were 1.75% of total hours worked in 1948 and fell to 0.5% by 2006.

FIG. 6. Private Business Hours versus Total Hours Worked (Divided by Noninstitutional Population 16 and Over).

One might think the standard measure compensates in part because it omits the military from both the numerator and the denominator. However, the trends in military hours go in the opposite direction of overall government hours. After the rise during the Korean War to 5%, military hours as a fraction of total hours have trended downward, with a small blip during the Vietnam War. Currently, military hours are only 1% of total hours worked.

Figure 5B shows hours in the nonprofit sector as a fraction of total hours worked. This series does not count volunteer hours, only paid hours. The fraction of hours worked in the nonprofit sector rises steadily from 2.5% in 1948 to 8% in 2006. Much of this increase is due to the growth of the medical care and education sectors, since half of the hospitals and universities are categorized as nonprofit.[5]

Figure 5C shows private business hours as a percentage of total hours. Hours worked in private business represented 86% of all hours worked in 1948 but have fallen to only 76% of all hours worked. It is clear that the trends in private business hours per capita are in part due to its falling share of total hours worked.

Figure 6 compares the standard measure, which is private business hours divided by the civilian noninstitutional population ages 16 and over, to total hours worked divided by the noninstitutional population (including the armed forces) ages 16 and over. Whereas the peak of the private hours series in 1973 is over 13% below the peak in 1948, the peak of the total hours series in 1973 is only 5% below the peak in

5. See Salamon and Sokolowski (2005) for a description of the growing importance of the nonprofit sector.

1948. Thus, some of the low-frequency movements disappear when we use a more complete measure of hours worked.

3. THE EFFECTS OF DEMOGRAPHIC TRENDS

We now present evidence that demographic trends are an additional source of the low-frequency movements in hours and productivity. We begin by presenting empirical evidence that prime age individuals have very different labor market behavior than nonprime age individuals. In particular, we show that prime age individuals work more hours and are more productive than younger and older individuals. These microeconomic facts have macroeconomic implications once they are coupled with the changing share of prime age individuals in the working-age population. We then present a simple theoretical model showing how these movements can invalidate Galí's (1999) identifying assumptions for technology shocks.

3.1 Empirical Evidence

Figure 7A uses Census data to show average weekly hours worked by age group for 1950, 1980, and 2000. (The Data Appendix describes how we used individual Census data from integrated public use microdata series [IPUMs] to derive these estimates.) The graph shows that those under age 22 and those over age 65 work much less than

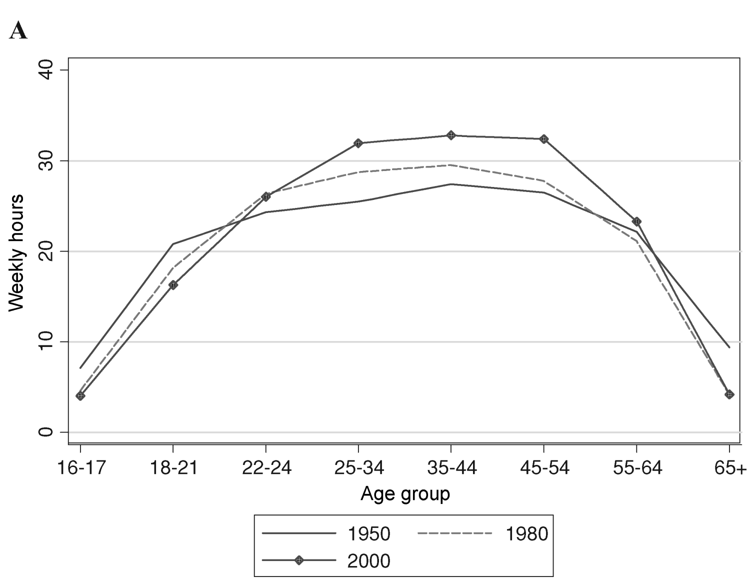


FIG. 7. (A) Average Weekly Hours Worked by Age Group (Based on Census Data Using the Noninstitutional Population).

B

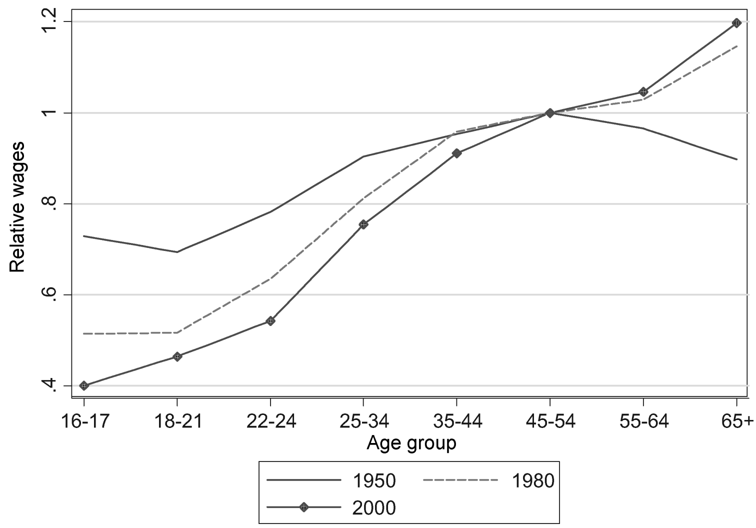


FIG. 7. (B) Wages by Age Group Relative to Wage of those Ages 45–54 (Based on Census Data, Excluding the Self-Employed).

individuals between ages 22 and 64. From 1950 to 2000, the average hours worked by those ages 16–21 and those 65 and over have fallen. The fall in hours among the young is due in part to the increased propensity to go to college (see Ramey and Francis 2009). In contrast, the average hours worked by those ages 22–54 has risen. This rise is due to the increased labor force participation rates of women. Thus, the age differences in hours worked have become even more stark over time.

Wages also differ across age groups, as demonstrated in Figure 7B. (The Data Appendix describes how we use Census data to calculate wages by age group.) Wages are shown relative to those ages 45–54. According to these estimates younger workers are much less productive than workers ages 45–54. For example, in 2000 an individual 22–24 years of age was only half as productive as an individual 45–54. In 1950, workers ages 65 and over were less productive than workers ages 45–54, whereas in 1980 and 2000 they were more productive.

If the age composition of the population stayed constant, these differences in hours and wages by age group would not lead to trends in per capita hours. However, as Figure 8 shows, the shares of these age groups have changed over time. Figure 8A shows the fraction of the population (ages 16 and over) that is between ages 16 and 21. The effect of the baby boom is very clear. The fraction rose from 11% in mid-1950s to almost 16% in the mid-1970s, and then fell so that it is now below 11%. Figure 8B shows the steady increase in the fraction of 16 and older population that is ages 65 and older. This fraction has risen from 10% to 16% during the post-WWII period. Figure 8C shows the fraction of the population ages 16 and over that is between the

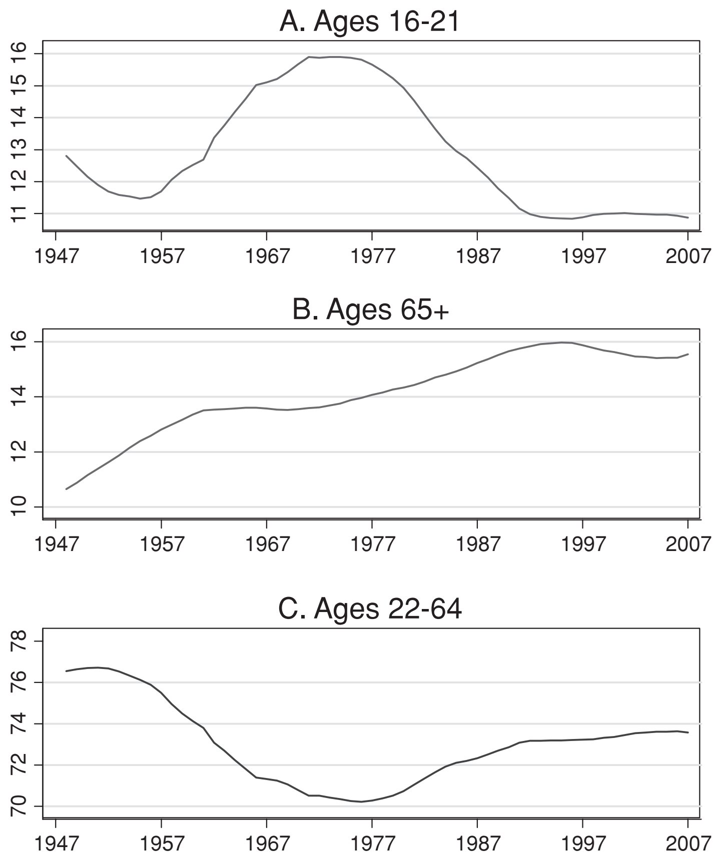


Fig. 8. Age Composition of Population (Percentage of Population Ages 16 and Over).

ages of 22 and 64. It starts above 76% at the start of the sample, falls to 70% in the mid 1970s, and is now at 73%. Note the similarity of this pattern to the HP-filtered trend of the standard measure of hours per capita shown in Figure 3.

3.2 The Theoretical Effects of Demographic Trends

Can changes in the age composition of the population lead to low-frequency movements in hours worked and productivity? We now present a simple model that shows that they can affect the steady-state values of both of these variables. We consider an economy with two types of workers who differ only in their productivity and consider the effects of variations in the fraction of those workers.

Following Jaimovich, Pruitt, and Siu (2009), we construct a model in which the representative household has two types of workers: Type A ("prime age") and Type B ("young and old"). Type B workers differ from Type A workers in that they have lower productivity. We capture these ideas parsimoniously as follows. A representative household maximizes the present discounted value of utility

$$\sum_{t=0}^{\infty}\beta^t\left\{\ln(c_t)-\varphi\left[s_A\frac{h_{At}^{1+\theta}}{1+\theta}+(1-s_A)\frac{h_{Bt}^{1+\theta}}{1+\theta}\right]\right\},\quad 0\leq s_A\leq 1,\varphi>0,\theta\geq 0, \tag{1}$$

where c_t is per capita consumption of each family member, s_A is the share of family members of Type A, h_A is the per capita hours worked of Type A family members, and h_B is the per capita hours worked of Type B family members.

The production function of the representative firm is given by

$$Y_t=(Z_tH_{et})^{\alpha}K_t^{1-\alpha},\quad \text{with}\quad H_{et}=s_Ah_{At}+(1-s_A)\chi h_{Bt}. \tag{2}$$

Output is Cobb–Douglas in efficiency hours H_e and capital K, and productivity Z is labor augmenting. Efficiency hours are the sum of the effective hours of each type of worker. However, we assume that Type B workers are less productive, so that an hour of work by Type B workers is equivalent to fraction χ of a Type A worker hour. That is, we assume that $0<\chi<1$.

The economy's resource constraint is given by

$$Y_t=C_t+I_t, \tag{3}$$

with capital accumulation equation

$$K_{t+1}=(1-\delta)K_t+I_t. \tag{4}$$

For simplicity, we normalize the population to unity, so that per capita values are the same as aggregate values and assume that the mean growth rate of technological change is γ. Then we transform the model by dividing key variables by Z_t so that we can analyze steady-states. Let smaller case variables with hats stand for the transformed variables, for example, $\hat{k}_t=\frac{K_t}{Z_t}$. The key steady-state equations for our model are

$$1-\delta+(1-\alpha)\left(\frac{\hat{k}}{H_e}\right)^{-\alpha}=\frac{1+\gamma}{\beta}\quad \text{marginal product of capital,} \tag{5}$$

$$H_{et}=s_Ah_{At}+(1-s_A)\chi h_{Bt}\qquad \text{definition of efficiency hours,} \tag{6}$$

$$H_t=s_Ah_{At}+(1-s_A)h_{Bt}\qquad \text{definition of aggregate hours,} \tag{7}$$

$$\frac{Y}{H_e}=Z\cdot\left(\frac{\hat{k}}{H_e}\right)^{1-\alpha}\qquad \text{labor productivity in efficiency units,} \tag{8}$$

$$\frac{Y}{H} = Z \cdot \frac{H_e}{H} \cdot \left(\frac{\hat{k}}{H_e}\right)^{1-\alpha} \qquad \text{labor productivity in unadjusted units,} \tag{9}$$

$$\varphi h_A^{\theta} = \alpha \frac{Y}{C} \cdot \frac{1}{H_e} \qquad \text{marginal rate of substitution for Type A,} \tag{10}$$

$$\varphi h_B^{\theta} = \alpha \chi \frac{Y}{C} \cdot \frac{1}{H_e} \qquad \text{marginal rate of substitution for Type B,} \tag{11}$$

$$\frac{I}{Y} = (\gamma + \delta)\left(\frac{\hat{k}}{H_e}\right)^{\alpha} \qquad \text{investment rate,} \tag{12}$$

$$\frac{C}{Y} = 1 - \frac{I}{Y} \qquad \text{consumption share.} \tag{13}$$

It is clear from equation (5) that the capital–efficiency hours ratio is determined by the usual parameters $\delta, \beta, \gamma,$ and α, and thus is invariant to changes in the share of Type A workers (s_A) or the relative productivity (χ). Equations (8) and (9) show that this model is consistent with the identifying assumption used in the empirical work *only if productivity is defined in efficiency hours*. Y/H_e depends only on technology Z, but Y/H depends both on technology Z and the ratio of efficiency hours to aggregate hours. Thus, in this model long-run changes in the demographics can have effects on steady-state productivity.

Equations (10) and (11) show that average hours worked by Type A workers are greater than average hours worked by Type B workers (since χ is less than unity). Similarly, the wage of Type A workers is greater than the wage of Type B workers. Thus, this model captures the salient cross-sectional facts about prime age workers versus nonprime age workers.

It is easy to manipulate the equations above to show the following additional results. A fall in the share of Type A workers, s_A

(i) Reduces labor productivity defined in terms of aggregate hours (the standard measure).
(ii) Does not change labor productivity defined in terms of efficiency hours.
(iii) Reduces aggregate hours worked per capita (H) as long as $s_A > 0.5$.

The reason that result (iii) depends on parameter values is that a fall in s_A has a pure negative wealth effect, leading to a rise in hours of each type of worker. However, as long as s_A is above 0.5 (a sufficient but not necessary condition), the composition effect outweighs the wealth effect.[6]

6. Details behind these results are available from the authors upon request.

Thus, this simple model makes clear our point that demographics can induce positive correlations between hours worked per capita and productivity that have nothing to do with technology. A decline in the fraction of prime age workers would be expected to reduce both productivity and aggregate hours.

4. NEW MEASURES OF HOURS PER CAPITA AND PRODUCTIVITY

We now use the empirical and theoretical insights from the last sections to construct measures of hours per capita and productivity that correct for demographics and sectoral shifts. We correct for sectoral shifts simply by using aggregate hours rather than just private business hours as our measure. Figure 6 already showed that a significant amount of the low-frequency movements of the standard measure of hours per capita was due to the use of only private business hours rather than aggregate hours in the numerator.

To correct for demographics, we adjust average hours worked for demographics and convert productivity to an efficiency hours basis. Following Shimer (1998), we eliminate demographic influences on average weekly hours worked using the following formula

$$\bar{H}_t = H_t - \sum_{\tau=t_0}^{t}\left[\sum_{i=1}^{8}\left(\frac{h_{i\tau} + h_{i\tau-1}}{2}\right)(\theta_{i\tau} - \theta_{i\tau-1})\right], \tag{14}$$

where $\bar{H}_t$ is adjusted average weekly hours, H_t is unadjusted average weekly hours per capita, h_{it} is average weekly hours per capita worked by group i in period t, and θ_{it} is age-group i's share of the noninstitutional population ages 16 and over. The double-summation term is the cumulative chain-weighted changes in hours due to demographics. The eight age groups are 16–17, 18–21, 22–24, 25–34, 35–44, 45–54, 55–64, and 65+. The Data Appendix gives details of the data sources and calculations.

In order to adjust productivity for demographic movements, we create a quality-adjusted labor input series, such as in Jorgenson, Gollop, and Fraumeni (1987) and Hansen (1993). We use a Tornqvist index to aggregate the quality-weighted growth rates of hours of each age group as follows:

$$\Delta \ln L_t = \sum_{i=1}^{8}\left(\frac{v_{i\tau} + v_{i\tau-1}}{2}\right)\Delta \ln H_{it}. \tag{15}$$

Here, L_t is effective labor input, v_{it} is age group i's share of the wage bill, and H_{it} is total hours worked by age group i in period t. The growth rate of L_t is cumulated to obtain an index of the level. This series is then used with real gross domestic product (GDP) to construct labor productivity. The Data Appendix gives full details on the construction of these series.

In two related papers, Feyrer (2007, 2008) shows that demographic shifts are important factors in explaining movements in aggregate productivity. In particular, Feyrer

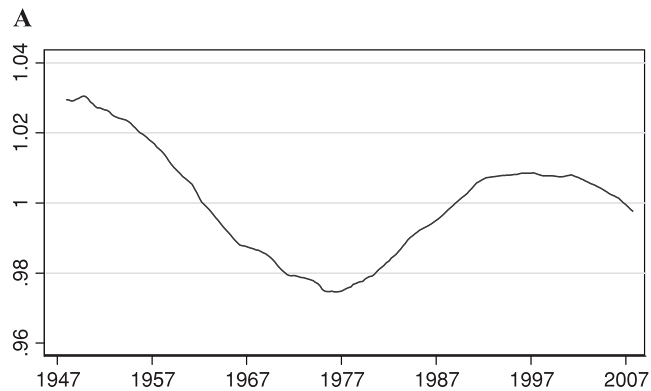


FIG. 9. (A) Ratio of Actual Weekly Hours per Capita to Demographically Adjusted Weekly Hours.

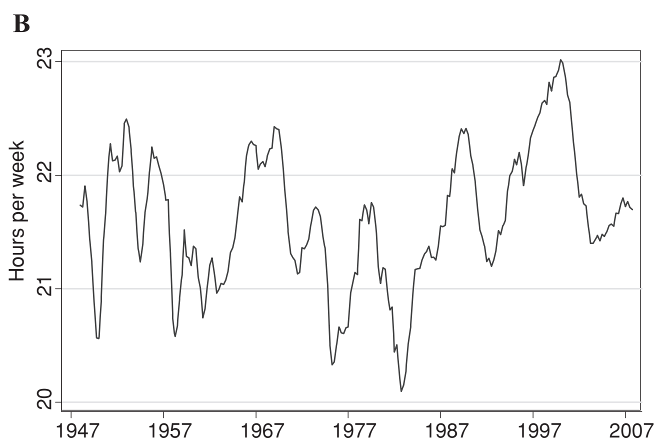


FIG. 9. (B) Demographically Adjusted Weekly Hours per Capita.

(2007) demonstrates that changes in workforce demographics have a strong and significant correlation with the growth rate of productivity and that an increase in the proportion of workers between the ages of 40 and 49 is associated with positive productivity growth.[7]

Figure 9A shows the ratio of average weekly hours of the noninstitutional population ages 16 and over to our demographically adjusted weekly hours.[8] As the graph

7. Feyrer's works also demonstrate that demographics can partially explain U.S. productivity shifts over time and the persistent productivity gap between the Organisation for Economic Co-operation and Development (OECD) and low-income countries.

8. We have normalized our adjusted series so that it has the same mean as the unadjusted series.

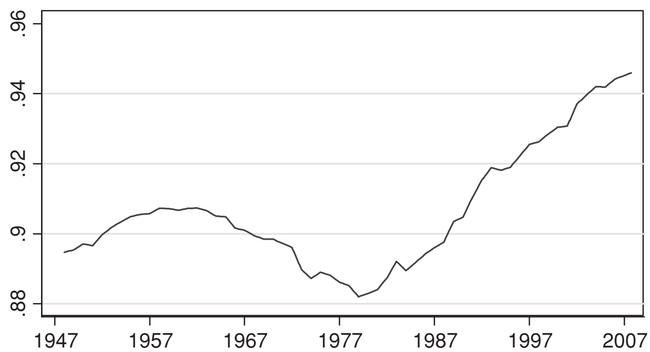


FIG. 10. Ratio of Efficiency Hours to Total Hours (Efficiency Hours are Based on Tornqvist Weights).

shows, the ratio was quite high in the late 1940s and 1950s, but then fell during the 1970s, with some recovery during the 1990s. The pattern shown in this graph mimics the U-shape in the standard measure of hours per capita. Figure 9B shows the effect of using the demographically adjusted weekly hours based on total hours. It is evident from the graph that the U-shape mostly disappears. However, adjusted hours per capita were unusually high during the late 1990s.

Figure 10 shows the ratio of efficiency hours, constructed using a Tornqvist index, to total hours. This ratio shows a trough in the 1970s, just as predicted by our theory. It also shows a dramatic rise during the last 15 years.

5. THE EFFECTS OF TECHNOLOGY SHOCKS USING THE NEW MEASURE OF HOURS PER CAPITA

5.1 Baseline Impulse Responses

We now investigate how the use of our new measures of hours per capita and productivity based on efficiency hours changes the previous results on the effect of technology on hours. We reestimate the SVAR used by Galí (1999), Francis, and Ramey (2005), and CEV using the productivity measure based on efficiency hours and the adjusted hours per capita. The left panel of Figure 11 plots the impulse responses from the system. Per capita labor hours respond negatively, and significantly, in the short run to the technology shock. Hours become slightly positive, though not significantly so, after a year or more.

We also controlled for demographics in a less structured manner. In particular, we first regressed unadjusted labor productivity (real GDP divided by total hours for the entire economy) and aggregate labor hours per capita (total hours divided by noninstitutional population 16 and over) on demographic variables. The demographic variables are the fraction of the noninstitutional population ages 16 and over that are in each of the eight age groups, namely, those aged 16–17, 18–21, 22–24, 25–34, 35–44, 45–54, 55–64, and 65+. We then use the residuals from these regressions in the

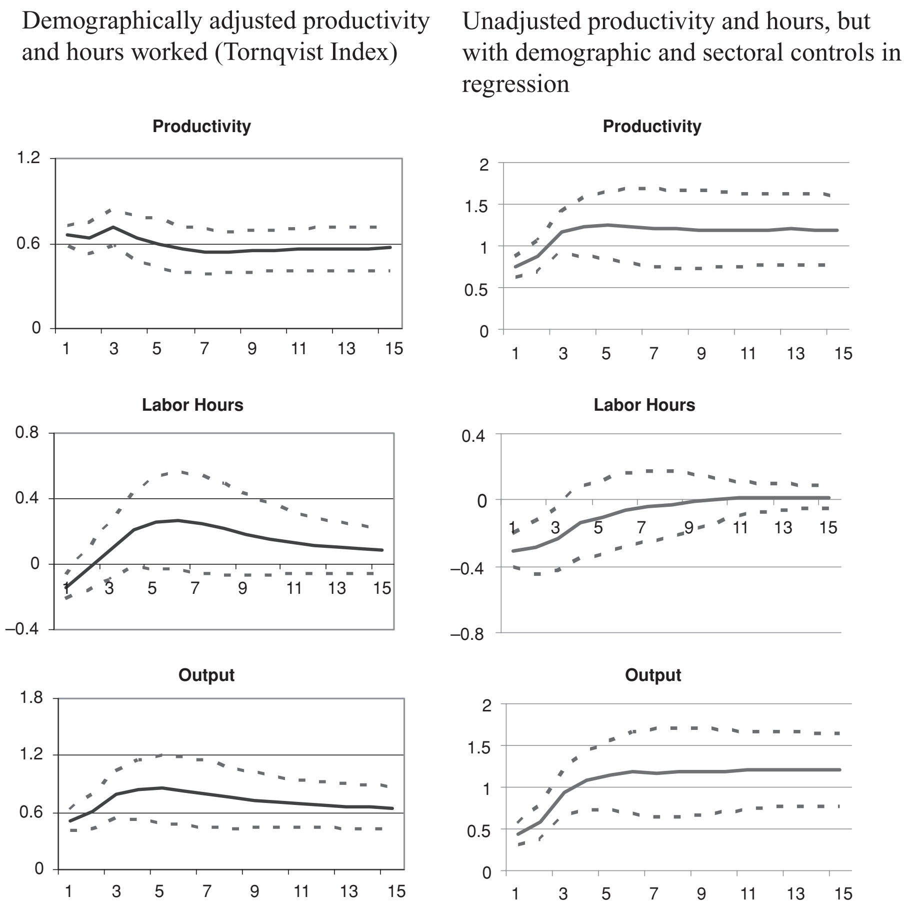


FIG. 11. Impulse Responses to a Technology Shock: Quarterly 1948–2007 (Total Economy, Hours in Levels, 95% Standard Error Bands).

SVAR. This method does not use the relative hours and wage rates, and hence does not impose assumptions about relative productivities and relative hours across age groups. The right panel of Figure 11 plots the impulse responses to a positive technological innovation. Again we see a significant initial drop in labor hours in response to the technology shock—productivity and output having their usual positive responses.

Thus, as in the first-differenced and HP-filtered cases, we find that hours respond negatively to technology shocks when we control for sectoral and demographic shifts over the sample period. These results also shed light on the debate concerning the results with the standard measure. There are important slow-moving demographic shifts, independent of technology, which if not accounted for will distort the results from our SVARs. By explicitly accounting for these demographics in the model and the data we get impulse responses consistent with Galí (1999) and Francis and Ramey (2005). Note that, by first differencing the data, Galí and Francis and Ramey essentially mitigate the extent of the effects that these slow-moving demographics have on the results.

5.2 Robustness Checks

We check robustness in several ways. First, we compute a variable-weight series of efficiency hours in which we use relative wages to convert hours of each age group to be equal to those of a 45- to 54-year-old in that year. In particular, the effective hours series is given by

$$L_t = \sum_{i=1}^{8} \omega_{it} H_{it}, \tag{16}$$

where ω_{it} is the average wage of group i relative to the average wage of group 45–54. The Data Appendix discusses the data construction. Using this efficiency hours in productivity (instead of the Tornqvist measure), along with demographically adjusted hours worked, delivers a persistent negative response of labor to a technology shock (see left panel of Figure 12). We also investigated using fixed weight series for both efficiency hours and demographically adjusted hours worked. Those results (not shown to conserve space) are similar the ones shown in the left panel of Figure 12.

Second, we investigated which adjustment was the most important, the adjustment to average hours or the adjustment to productivity. We found that when we used adjusted hours worked, but standard productivity measures, the impact on hours was still negative for two quarters, but the effects were smaller in magnitude. On the other hand, if we used standard hours worked with the efficiency measure of productivity, the impact on hours was zero or positive in every period. Thus, the adjustment to hours is more important than the adjustment to productivity in producing the negative impact of technology on hours.

In order to compare our results to the majority of results in the literature, we also test for robustness assuming that technology shocks originate from the private sector only. In the right panel of Figure 12 we preregressed the standard measures of private productivity and private hours on the fraction of the noninstitutional population ages 16 and over for the eight age groups, 16–17, 18–21, 22–24, 25–34, 35–44, 45–54, 55–64, and 65+. The detrending regression also includes the HP-filtered trend of the ratio of private to total hours as a regressor to capture any sectoral shift over the sample period.[9] Using the residuals from these regressions in the VAR we again find that hours fall significantly on impact to the technology shock.

9. We use the HP-filtered trend in so that we are not removing business-cycle-related fluctuations in the shares of the various sectors.

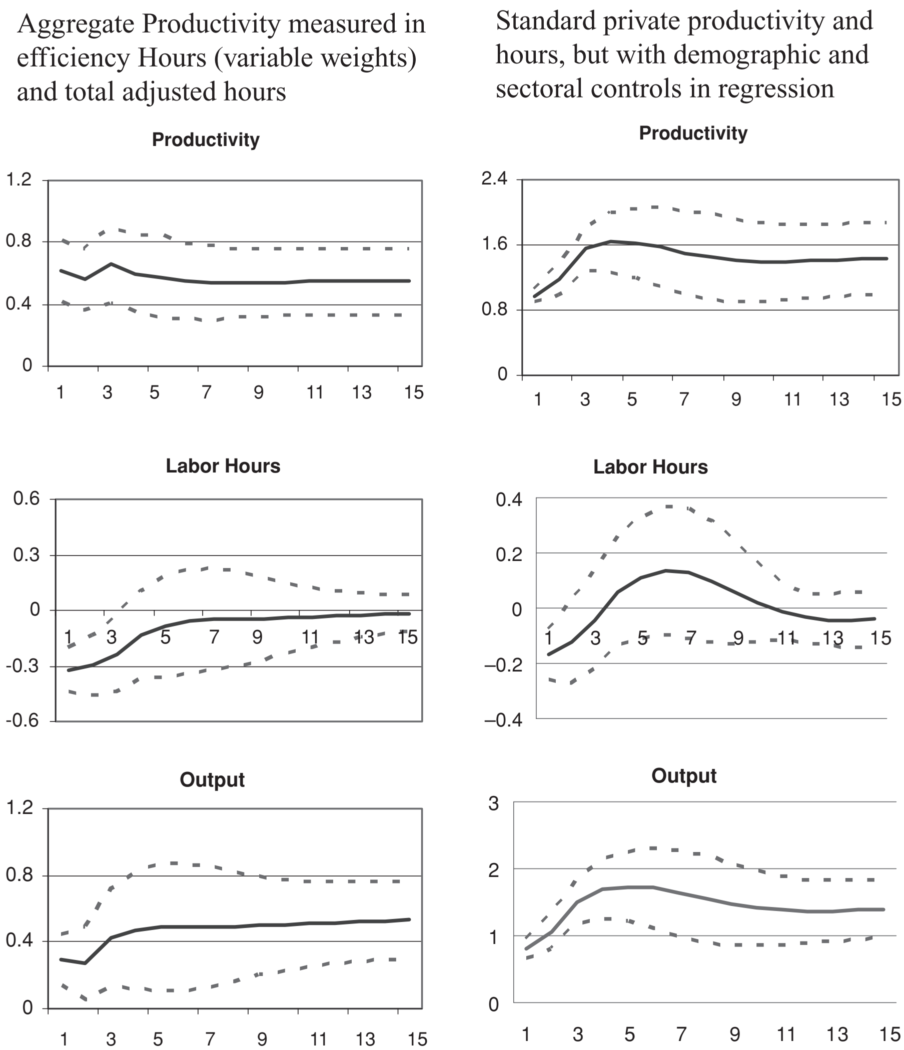


Fig. 12. Impulse Responses to a Technology Shock: Quarterly 1948–2007 (Aggregate [Left], Private [Right] Hours in Levels with 95% Standard Error Bands).

6. INVESTMENT-SPECIFIC TECHNOLOGY

Fisher (2006) has argued that investment-specific technological change leads to a positive response of labor hours. Fisher reached this conclusion after estimating a VAR that assumed that only the investment-specific technology shock (I-shock) can have any long-run impact on investment prices, and that the said I-shock and a neutral technology shock can both have long-run effects on labor productivity.

To determine whether Fisher's (2006) results are also sensitive to low-frequency sectoral and demographic trends, we reestimate a version of his model. Because Fisher argued for the inclusion of monetary variables in the VAR, we include both the federal funds and the inflation rates in the VAR. Our sample period covers from 1954:1 to 2000:4—1954:1 is the first period that we have data on the federal funds rate, while observations on equipment prices restrict the sample to end at 2000:4.

How does controlling for demographic and sectoral shifts affect the impulse responses to investment-specific technology shocks? Before we attempt to answer this question we include additional controls for low-frequency movements in the growth rate of equipment prices as highlighted by Canova, Lopez-Salido, and Michelacci (2007). We remove these low-frequency components by allowing for regime changes in the average growth rate of equipment prices in 1973:2 and again in 1997:1. That is, we use dummy variables that enable different intercepts over the different regimes in each equation of the VAR.[10] However, the slope coefficients are the same across the different regimes.

Figure 13 plots the impulse responses of productivity and hours to a positive I-shock for three specifications. Panel A of the figure shows the responses of productivity and hours using standard private sector measures. The impulse responses resembles those presented in Fisher (2006)—productivity declines for an extended period and hours rise significantly on impact.

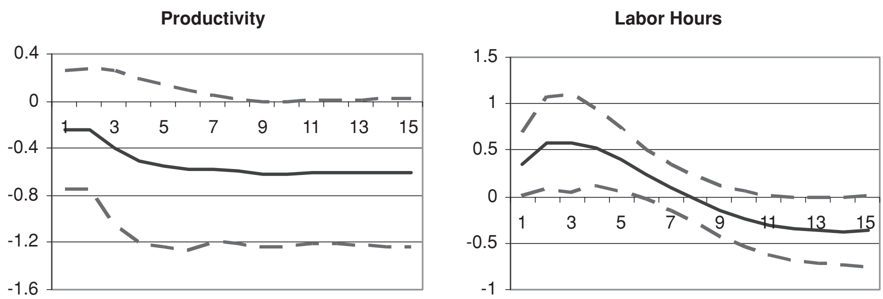
In Panel B, we plot the responses of productivity and hours using total efficiency hours and total adjusted hours. The impulse responses are similar to those presented in Panel A but there is now less uncertainty surrounding the negative productivity response.

Finally in Panel C, we plot the responses of standard private measures (used in Panel A) preregressed on the demographic variables and the HP-filtered trend in private business hours as a fraction of total hours. Qualitatively, the results are dramatically different from the previous results in the top panels and majority of the literature in general. In particular, there is a protracted positive response of labor productivity. We consider this more plausible than the negative responses in the top panels, as it is our belief that labor will eventually become more productive after learning the new technology embodying existing or new capital goods. In the top panels there is no tendency for labor productivity to become positive soon. Finally, labor hours now respond significantly negative to the I-shock, opposite that of Fisher (2006) and others. It should be noted, however, that in all three specifications hours and productivity move in the opposite direction.

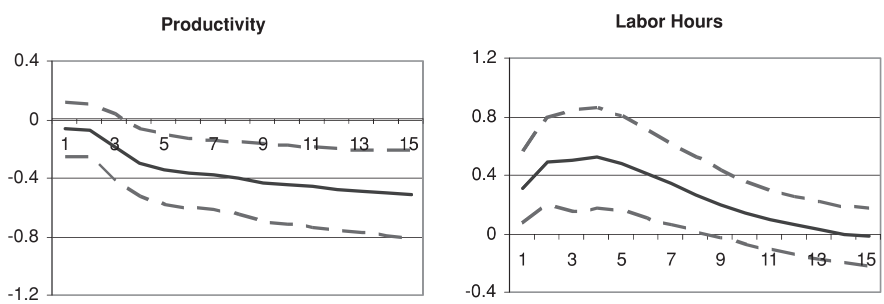
In summary, we conclude that demographic and sectoral trends affect the nature of impulse responses to I-shocks. However, the results crucially depend on how we control for the low-frequency movements characterizing these trends.

10. We find our results to be insensitive to the exclusion of the Canova, Lopez-Salido, Michelacci (2007) low-frequency dummies once we include our demographic controls.

Panel A. Standard private sector measures of productivity and hours



Panel B. Total productivity based on efficiency hours and total adjusted hours



Panel C. Standard private sector measures of productivity and hours pre-regressed on demographic and sectoral trends

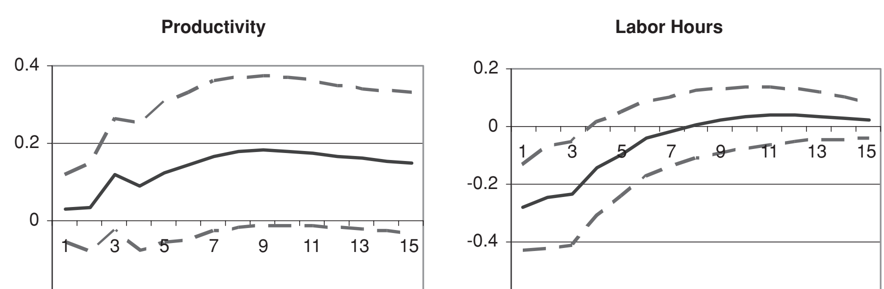


FIG. 13. Impulse Responses to a Positive Investment-Specific Technology Shock: Quarterly 1954–2000 (Both Private and Total Economy, Hours in Levels with 95% Standard Error Bands).

7. CONCLUSION

In this paper, we have proposed that the conflicting results in the debate concerning the effects of technology shocks on hours stems from the low-frequency movements in the standard measure of hours per capita. We first showed that removal of the low-frequency movements using a very conservative HP filter produces results suggesting a positive technology shock lowers hours in the short run. We then argued that the HP filter is capturing demographic and institutional changes, which have nothing to do with the kinds of technology shocks typically modeled in RBC theory. We modify standard theory to account for these changes and use the insights from the theory to produce a new measure of hours per capita and productivity that adjusts for these changes. Our measure, which adjusts for trends in government and nonprofit employment and the age structure of the population, removes most of the low-frequency trend in hours. We find that removing these slow-moving components leads to consistent results on the effects of technology on per capita hours worked, regardless of the stationary assumption assumed for per capita labor hours. That is, in contrast to results using the standard measure, once we control for demographic shifts our labor measure produces consistently negative effects of technology on hours, without any further need to econometrically manipulate the labor series.

We also tested the implications of controlling for the demographic and sectoral shifts on the responses to investment-specific technology shocks recently suggested as a viable alternative to neutral technology shocks. Here our conclusions are less conclusive and depend on how we employ these controls.

Finally, our findings also have direct implications for the nature of the "preference shock" identified by researchers such as Fernández-Villaverde and Rubio-Ramírez (2007) and Kahn and Rich (2007). Their "preference shock" is a catchall for anything that shifts relative labor supply and is not a typical stationary i.i.d. stochastic process. Our findings imply that it is easily measured demographic and institutional changes rather than mysterious "preference shocks" that are the source of these important low-frequency trends.

DATA APPENDIX

Aggregate Hours

We use published and unpublished data from the BLS on hours worked in private business, government, nonprofit, and private households. Shawn Sprague kindly provided the unpublished data.

Population

Annual data by 5-year ages groups are from *Historical Statistics Millenium Online Edition,* updated with recent reports from the Census website. We split these into smaller age groups as follows. We assumed the population ages 16–17 was two-fifths of the population ages 15–19, the population ages 18–21 was two-fifths of the population 15–24, and the population ages 22–24 was three-fifths of the population ages 20–24. To convert to noninstitutional population, we calculate decennial institutionalization rates from the IPUMS version of the Census (Ruggles et al. 2004) and interpolate to annual. We interpolate the annual population figures to quarterly.

Average Hours and Wages by Age

We use Census data from IPUMS to calculate hours worked by age group. For 1950, we use the variable "hrswork1." For 1980 and 2000, we calculate average weekly hours as uhrswrk $*$ wkswork1/52.

For wages, we limit the sample to those who are neither self-employed nor unpaid family workers. Wages are defined as incwage/hours, where hours are constructed as discussed above.

Adjusted Average Hours Worked

The fraction of the population in each age group is calculated based on the population data described above. Average hours by age group, which are used to weight the changes in fraction of population, are calculated from the decennial Census from IPUMs and then interpolated to quarterly. The 1960 and 1970 Census did not include military hours, so we used unpublished BLS data on military hours to create average hours worked.

Efficiency Hours

We measure the log change in hours by age group by multiplying total hours by our estimate of the fraction of hours worked by each age group. We estimate the hours fraction as follows. For civilian hours, we use several data sources. For 1962 on, we use the March Current Population Survey (CPS) for the annual data on civilian hours by age group. Before 1962, we use the following procedure. First, we use the 1950 and 1960 Census to calculate hours per worker for each age group and interpolate. We then apply these series to the BLS employment by age group series for March of each year, available from the BLS website, to give us total hours by age group. We then combine Census data on military employment by age with the BLS's unpublished series on military hours to add these hours fractions to civilian hours to obtain total hours fractions. For the wage bill weights, we interpolated Census wage data discussed above, combined with the hours information. We did not use the CPS to calculate annual wages because the small sample sizes led to erratic estimates.

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