Online Appendix to

"Revisions in Utilization-Adjusted TFP Robust Identification of News Shocks"*

André Kurmann
Drexel University

Eric Sims
University of Notre Dame
& NBER

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This appendix provides additional details and supporting material for "Revisions in Utilization-Adjusted TFP and Robust Identification of News Shocks". Section 1 reports additional results on the revisions in Fernald's adjusted TFP series. Section 3 describes in more detail the medium-scale DSGE model used in the paper for Monte Carlo simulations. Section 4 documents the robustness of the max-share identification approach to alternative measures of productivity, in particular unadjusted TFP and labor productivity. Section 5 shows additional Monte-Carlo results for the max-share identification.

1 Additional results on revisions in adjusted TFP

To further illustrate that the revisions in adjusted TFP occur primarily because of changes in estimated utilization and not changes to unadjusted TFP, we create synthetic series of adjusted TFP by combining different vintages of unadjusted TFP with estimated utilization from a given vintage. Table 1 shows the results. The correlations of the different synthetic series with the actual series are always above 0.9. In particular, the correlation of $\left(\Delta \ln TFP_t^{14} - \Delta \ln \hat{u}_t^{07}\right)$, respectively $\left(\Delta \ln TFP_t^{16} - \Delta \ln \hat{u}_t^{07}\right)$ with $\Delta \ln TFP_t^{U,07}$ is 0.91, compared to 0.56 and 0.58 for the actual 2014 and 2016 vintages (i.e. the ones computed with the 2014 and 2016 estimate of utilization). See Table 2 in the main text.

*Kurmann: Drexel University, LeBow College of Business, School of Economics, 3220 Market Street, Philadelphia, PA 19104 (email: kurmann.andre@gmail.com); Sims: University of Notre Dame, 3060 Jenkins Nanovic Hall, Notre Dame, IN 46556 (esims1@nd.edu).

Table 1: Correlations of synthetic utilization-adjusted TFP series

	$\Delta \ln TFP_t^{07} - \Delta \ln \hat{u}_t^{07}$	$\Delta \ln TFP_t^{13} - \Delta \ln \hat{u}_t^{07}$	$\Delta \ln TFP_t^{14} - \Delta \ln \hat{u}_t^{07}$	$\Delta \ln TFP_t^{16} - \Delta \ln \hat{u}_t^{07}$
Corr w/ $\Delta \ln TFP_t^{U,07}$	1.00	0.91	0.91	0.91
	$\Delta \ln TFP_t^{07} - \Delta \ln \hat{u}_t^{13}$	$\Delta \ln TFP_t^{13} - \Delta \ln \hat{u}_t^{13}$	$\Delta \ln TFP_t^{14} - \Delta \ln \hat{u}_t^{13}$	$\Delta \ln TFP_t^{16} - \Delta \ln \hat{u}_t^{13}$
Corr w/ $\Delta \ln TFP_t^{U,13}$	0.91	1.00	1.00	1.00
	$\Delta \ln TFP_t^{07} - \Delta \ln \hat{u}_t^{14}$	$\Delta \ln TFP_t^{13} - \Delta \ln \hat{u}_t^{14}$	$\Delta \ln TFP_t^{14} - \Delta \ln \hat{u}_t^{14}$	$\Delta \ln TFP_t^{16} - \Delta \ln \hat{u}_t^{14}$
Corr w/ $\Delta \ln TFP_t^{U,14}$	0.93	1.00	1.00	1.00
	$\Delta \ln TFP_t^{07} - \Delta \ln \hat{u}_t^{16}$	$\Delta \ln TFP_t^{13} - \Delta \ln \hat{u}_t^{16}$	$\Delta \ln TFP_t^{14} - \Delta \ln \hat{u}_t^{16}$	$\Delta \ln TFP_t^{16} - \Delta \ln \hat{u}_t^{16}$
Corr w/ $\Delta \ln TFP_t^{U,16}$	0.92	1.00	1.00	1.00

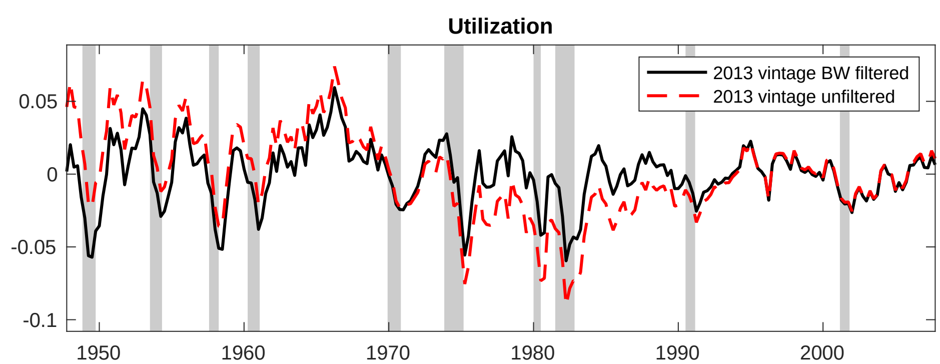
Notes: $\Delta \ln TFP_t^{U,j}$ is the quarterly log change expressed in annualized percentage points of Fernald's adjusted TFP series for vintages $j = 07$, 13, 14 or 16. All correlations are rounded to the nearest hundredth. The sample period for each of the statistics is 1947q3-2007q3.

To illustrate the effects of bi-weight filtering industry hours per worker in Fernald's construction of utilization, we compare it to utilization constructed without filtering hours per worker. Specifically, we take Fernald's replication code for the 2013 vintage and construct utilization as

$$\Delta \ln \hat{u}_t = \sum_i \kappa_i \widehat{\beta}_i \Delta \ln h_{it}^c, \tag{1}$$

where $\ln h_{it}^c$ is either bi-weight filtered or not filtered. Figure 1 shows the resulting demeaned utilization series. The unfiltered series is above the bi-weight filtered series until the mid-1960s and then declines below the bi-weight filtered series between the mid-1970s and the early 1990s. Aside from this very slow-moving difference, the quarter-to-quarter changes in the two series are almost identical. This is especially apparent for the last ten years of the sample. Indeed, the correlation between bi-weight filtered $\Delta \ln \hat{u}_t$ and unfiltered $\Delta \ln \hat{u}_t$ is 0.999. In other words, all that bi-weight filtering of hours does is to remove very slow-moving trends.

Figure 1: Estimated Utilization with Bi-weight and No Filtering

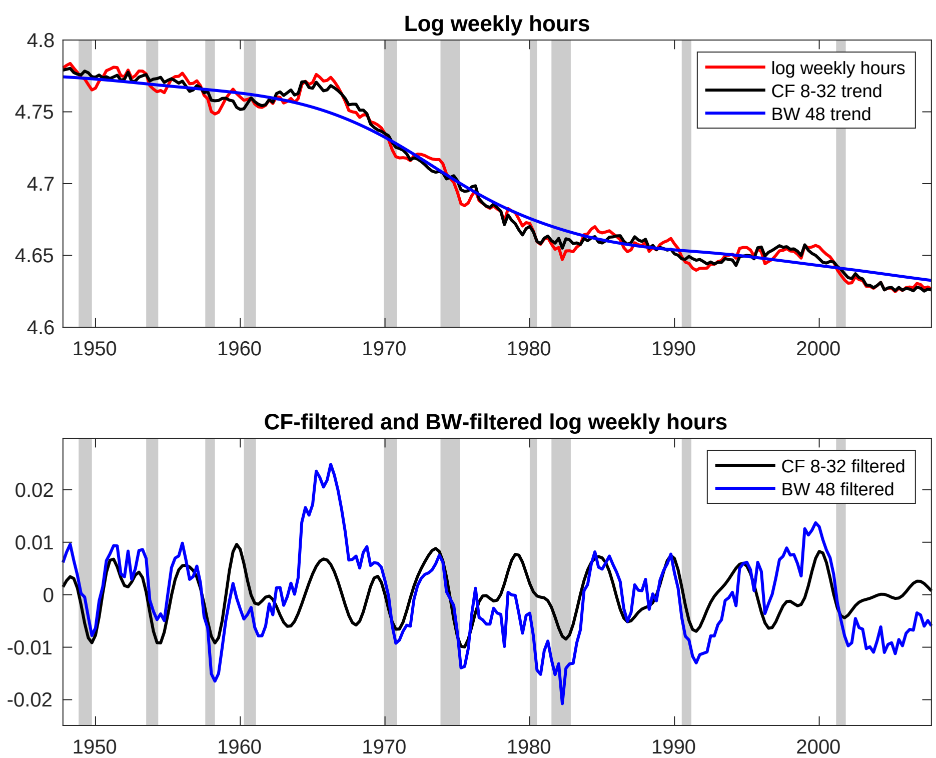


Notes: The figure plots the log levels of estimated utilization computed with the 2013 vintage of Fernald's data using bi-weight filtered industry hours (black solid line) and unfilterd industry hours (red dashed lines). The grey shaded bars show NBER recessions. The sample period for each of the series is 1947q3-2007q3.

To illustrate the effects of detrending hours per worker with either the bandpass filter or the bi-weight filter discussed in Section 2 of the main text, consider aggregate weekly hours. As shown in the top panel of Figure 2, log aggregate weekly hours in the U.S. non-farm business sector display a secular decline from the mid-1960s to the mid-1980s. The bi-weight filter removes a very slowing trend from this series whereas the bandpass filter removes a much more close fitting trend that contains much of the high-frequency fluctuations in weekly hours. As shown in the bottom panel, the detrended series resulting from bandpass filtering is much less volatile and smoother than the one resulting from bi-weight filtering. While industry hours per worker in Fernald's data do not all display the same secular trend as aggregate hours per worker (indeed, in some industries, hours per worker increase over time), this illustrates the effects that the two filtering methods have.

The Figure also provides an intuitive explanation for the results above: since the bi-weight filter removes a very smooth trend, essentially the only difference between estimated utilization constructed with bi-weight filtered hours and estimated utilization constructed with unfiltered hours is this smooth trend. Quarter-to-quarter changes in the two series are almost identical.

Figure 2: Effects of Detrending Hours per Worker



Notes: The top panel plots the log of weekly average hours in the U.S. non-farm business sector (red solid line) as well as the trends obtained with the Christiano-Fitzgerald 8-32 quarter bandpass filter (black solid line) and the bi-weight 48 quarter filter (blue solid lines). The bottom panel plots the resulting detrended series. The grey shaded bars show NBER recessions. The sample period for all the series is 1947q3-2007q3.

2 Business Cycle Correlations Implied by Different News Shocks

Table 2 shows the median business cycle statistics for consumption growth, total hours growth and inflation in the data and as implied by the four-variable Bayesian VAR estimates in the main text conditional on the

Barsky-Sims news shock. As discussed in the Section 3 of the main text, when the VAR is estimated with the 2007 vintage of adjusted TFP, the news shock implies that consumption and hours growth are negatively correlated. When the VAR is estimated with the 2016 vintage of adjusted TFP instead, the news shock implies that consumption and hours growth are positively correlated. These correlations are significantly different zero.

Table 2: Business Cycle Corrleations Implied by Barsky-Sims Shock

	$sdev(\Delta lnC_t)$	$sdev(\Delta \ln H_t)$	$sdev(\pi_t)$	$corr(\Delta \ln C_t, \Delta lnH_t)$	$corr(\Delta \ln C_t, \pi_t)$
Data	0.68	0.79	1.13	0.42	-0.09
Barsky-Sims shock (TFP 2007)	0.36	0.30	0.39	-0.56	-0.73
Barsky-Sims shock (TFP 2016)	0.44	0.18	0.27	0.27	-0.75

Notes: The sample period for each of the statistics is 1960q1-2007q3. The model statistics pertain to medians from the posterior distribution of each data series implied by the Barsky-Sims news shock. All results are rounded to two digits after the decimal point.

Table 3 shows the median business cycle statistics for consumption growth, total hours growth and inflation in the data and as implied by the four-variable Bayesian VAR estimates in the main text conditional on the max-share shock. As discussed in Section 5 of the main text, the correlation between consumption and hours growth is negatively correlated independent of the vintage of adjusted TFP used.

Table 3: Business Cycle Moments Implied by Max-Share Shock

	$sdev(\Delta lnC_t)$	$sdev(\Delta \ln H_t)$	$sdev(\pi_t)$	$corr(\Delta \ln C_t, \Delta lnH_t)$	$corr(\Delta \ln C_t, \pi_t)$
Data	0.68	0.79	1.13	0.42	-0.09
Max-share shock (TFP 2007)	0.43	0.25	0.60	-0.23	-0.73
Max-share shock (TFP 2016)	0.39	0.26	0.53	-0.34	-0.71

Notes: The sample period for each of the statistics is 1960q1-2007q3. The model statistics pertain to medians from the posterior distribution of each data series implied by the max-share shock. All results are rounded to two digits after the decimal point.

3 A Medium Scale DSGE Model

For the Monte Carlo experiments considered in the paper, we use as a laboratory a conventionally specified medium scale DSGE model. The model features sticky prices and wages, capital accumulation, habit formation in consumption, an investment adjustment cost, variable capital utilization, and a central bank which implements monetary policy according to a Taylor rule. The model is very similar to Christiano, Eichenbaum, and Evans (2005), Smets and Wouters (2007), and Justiniano, Primiceri, and Tambalotti (2010). So as to be consistent with the assumptions underlying Fernald's adjusted TFP series, the model is amended so as to allow for three different margins of labor adjustment – an extensive and intensive margin as well as labor effort. We only list the full set of equilibrium conditions here, rather than fully laying out the decision problems of each type of agent in the model.

The functional forms for the different adjustment costs are:

$$a(z_t) = \gamma_1(z_t - 1) + \frac{\gamma_2}{2}(z_t - 1)^2 \tag{2}$$

$$\Psi\left(\frac{N_t}{N_{t-1}}\right) = \frac{\psi}{2}\left(\frac{N_t}{N_{t-1}} - 1\right)^2 \tag{3}$$

$$J\left(\frac{I_t}{K_t}\right) = \frac{\varphi}{2}\left(\frac{I_t}{K_t} - \delta\right)^2 \tag{4}$$

The full set of equilibrium conditions are listed below. A brief discussion follows.

$$\lambda_t = \nu_t \left(C_t - bC_{t-1}\right)^{-1} - \beta b E_t \nu_{t+1} \left(C_{t+1} - bC_t\right)^{-1} \tag{5}$$

$$\lambda_t = \beta E_t \lambda_{t+1} R_t \Pi_{t+1}^{-1} \tag{6}$$

$$r_t^k = \gamma_1 + \gamma_2(z_t - 1) \tag{7}$$

$$\theta \nu_t \kappa_3 e_t^{\kappa_4 - 1} = \lambda_t w_t h_t \tag{8}$$

$$\theta \nu_t \kappa_1 h_t^{\kappa_2 - 1} = \lambda_t w_t e_t \tag{9}$$

$$\lambda_t \left[1 + \varphi\left(\frac{I_t}{K_t} - \delta\right)\right] = \xi_t \mu_t \tag{10}$$

$$\begin{aligned}\xi_t = \beta E_t \Bigg[\lambda_{t+1} \Bigg(& r_{t+1}^k z_{t+1} - \gamma_1(z_{t+1} - 1) - \frac{\gamma_2}{2}(z_{t+1} - 1)^2 \\ & - \frac{\varphi}{2}\left(\frac{I_{t+1}}{K_{t+1}} - \delta\right) + \varphi\left(\frac{I_{t+1}}{K_{t+1}} - \delta\right)\frac{I_{t+1}}{K_{t+1}}\Bigg) + \xi_{t+1}(1 - \delta)\Bigg]\end{aligned} \tag{11}$$

$$\begin{aligned}\theta \nu_t \left(\kappa_0 + \frac{\kappa_1}{\kappa_2} h_t^{\kappa_2} + \frac{\kappa_3}{\kappa_4} e_t^{\kappa_4}\right) = {} & \lambda_t w_t \left[e_t h_t - \frac{\psi}{2}\left(\frac{N_t}{N_{t-1}} - 1\right)^2 - \psi\left(\frac{N_t}{N_{t-1}} - 1\right)\frac{N_t}{N_{t-1}}\right] \\ & + \beta E_t \left[\lambda_{t+1} w_{t+1} \left(\frac{N_{t+1}}{N_t} - 1\right)\left(\frac{N_{t+1}}{N_t}\right)^2\right]\end{aligned} \tag{12}$$

$$\Lambda_{t,t-1} = \beta \frac{\lambda_t}{\lambda_{t-1}} \tag{13}$$

$$w_t^{\#} = \frac{\epsilon_w}{\epsilon_w - 1} \frac{f_{1,t}}{f_{2,t}} \tag{14}$$

$$f_{1,t} = w_t (w_t^l)^{\epsilon_w} L_{d,t} + \theta_w E_t \left[\Lambda_{t,t+1} g_Y^{-\epsilon_w - 1} \Pi_t^{-\epsilon_w \gamma_w} \Pi^{-\epsilon_w(1-\gamma_w)} \Pi_{t+1}^{\epsilon_w} f_{1,t+1}\right] \tag{15}$$

$$f_{2,t} = (w_t^l)^{\epsilon_w} L_{d,t} + \theta_w E_t \left[\Lambda_{t,t+1} g_Y^{-\epsilon_w} \Pi_t^{(1-\epsilon_w)\gamma_w} \Pi^{(1-\epsilon_w)(1-\gamma_w)\epsilon_w} \Pi_{t+1}^{\epsilon_w - 1} f_{2,t+1}\right] \tag{16}$$

$$r_t^k = \alpha mc_t A_t K_{s,t}^{\alpha-1} L_{s,t}^{1-\alpha} \tag{17}$$

$$w_t^l = (1-\alpha) mc_t A_t K_{s,t}^{\alpha} L_{s,t}^{-\alpha} \tag{18}$$

$$\Pi^{\#} = \frac{\epsilon_p}{\epsilon_p - 1} \frac{x_{1,t}}{x_{2,t}} \tag{19}$$

$$x_{1,t} = mc_t Y_t + \theta E_t \left[\Lambda_{t,t+1} \Pi_t^{-\epsilon_p \gamma_p} \Pi^{-\epsilon_p (1-\gamma_p)} \Pi_{t+1}^{\epsilon_p} x_{1,t+1} \right] \tag{20}$$

$$x_{2,t} = Y_t + \theta E_t \left[\Lambda_{t,t+1} \Pi_t^{(1-\epsilon_p)\gamma_p} \Pi^{(1-\epsilon_p)(1-\gamma_p)} \Pi_{t+1}^{\epsilon_p - 1} x_{1,t+1} \right] \tag{21}$$

$$Y_t v_t^p = A_t K_{s,t}^{\alpha} L_{s,t}^{1-\alpha} - X_t F \tag{22}$$

$$v_t^p = (1-\theta_p)(\Pi_t^{\#})^{-\epsilon_p} + \theta_p \Pi_{t-1}^{-\epsilon_p \gamma_p} \Pi^{-\epsilon_p (1-\gamma_p)} \Pi_t^{\epsilon_p} v_{t-1}^p \tag{23}$$

$$K_{t+1} = \mu_t I_t + (1-\delta) K_t \tag{24}$$

$$L_t = L_{s,t} v_t^w \tag{25}$$

$$v_t^w = (1-\theta_w) \left(\frac{w_t^{\#}}{w_t} \right)^{-\epsilon_w} + \theta_w g_Y^{-\epsilon_w} \Pi_{t-1}^{-\epsilon_w \gamma_w} \Pi^{-\epsilon_w (1-\gamma_w)} \Pi_t^{\epsilon_w} \left(\frac{w_t}{w_{t-1}} \right)^{\epsilon_w} v_{t-1}^w \tag{26}$$

$$Y_t = C_t + I_t + \frac{\psi}{2} \left(\frac{N_t}{N_{t-1}} - 1 \right)^2 mrs_t N_t + \frac{\varphi}{2} \left(\frac{I_t}{K_t} - \delta \right)^2 K_t + \left[\gamma_1 (z_t - 1) + \frac{\gamma_2}{2} (z_t - 1)^2 \right] K_t \tag{27}$$

$$K_{s,t} = z_t K_t \tag{28}$$

$$L_t = e_t h_t N_t \tag{29}$$

$$1 = (1-\theta_p)(\Pi_t^{\#})^{1-\epsilon_p} + \theta_p \Pi_{t-1}^{\gamma_p (1-\epsilon_p)} \Pi^{(1-\gamma_p)(1-\epsilon_p)} \Pi_t^{\epsilon_p - 1} \tag{30}$$

$$\left(w_t^l \right)^{1-\epsilon_w} = (1-\theta_w)(w_t^{\#})^{1-\epsilon_w} + \theta_w g_Y^{1-\epsilon_w} \Pi_{t-1}^{\gamma_w (1-\epsilon_w)} \Pi^{(1-\gamma_w)(1-\epsilon_w)} \Pi_t^{\epsilon_w - 1} \left(w_{t-1}^l \right)^{1-\epsilon_w} \tag{31}$$

$$R_t = R^{(1-\rho_R)} \left[\left(\frac{\Pi_t}{\Pi} \right)^{\phi_\pi} \left(\frac{Y_t / Y_{t-1}}{g_Y} \right)^{\phi_y} \right]^{1-\rho_R} \exp(s_R \varepsilon_{R,t}) \tag{32}$$

$$\ln \mu_t = \rho_\mu \ln \mu_{t-1} + s_\mu \varepsilon_{\mu,t} \tag{33}$$

$$\ln \nu_t = \rho_\nu \ln \nu_{t-1} + s_\nu \varepsilon_{\nu,t} \tag{34}$$

$$\ln S_t = \rho_S \ln S_{t-1} + s_S \varepsilon_{S,t} \tag{35}$$

$$\ln \Gamma_t - \ln \Gamma_{t-1} = (1-\rho_\Gamma) \ln g + \rho_\Gamma \left(\ln \Gamma_{t-1} - \ln \Gamma_{t-2} \right) + s_g \varepsilon_{g,t-q} \tag{36}$$

$$A_t = S_t \Gamma_t \tag{37}$$

In these equations λ_t is the Lagrange multiplier on the flow budget constraint of a household and ξ_t

is the Lagrange multiplier on the capital accumulation equation. C_t denotes consumption, Y_t output, I_t investment, K_t physical capital, and $L_{s,t}$ aggregate labor services used in production. L_t is aggregate labor services supply (the product of effort, hours, and physical units of labor); labor services supply and demand potentially differ due to wage dispersion, v_t^w. w_t is the real wage received by the household and r_t^k is the real rental rate on capital services. mrs_t is the wage received by households from supplying labor services to labor unions. z_t denotes capital utilization, with $K_{s,t} = z_t K_t$ denoting capital services. Π_t is the gross inflation rate and R_t is the gross nominal interest rate. $\Pi_t^{\#}$ is the optimal relative reset price of updating firms, and v_t^p is a measure of price dispersion across firms. $x_{1,t}$ and $x_{2,t}$ are auxiliary variables related to price-setting. mc_t is real marginal cost. w_t^l is the aggregate real wage paid by production firms. $w_t^{\#}$ is the reset real wage for a labor union given the opportunity to adjust its wage in a given period. $f_{1,t}$ and $f_{2,t}$ are auxiliary variables related to optimal wage-setting. S_t is a stationary technology shock, while Γ_t is a non-stationary technology shock. A_t is technology, which is the product of these two terms. μ_t is a shock to the marginal efficiency of investment and ν_t is an intermporal preference shock. X_t is a trend factor, to be discussed below. g_Y is the steady state gross growth rate of output. Variables without time subscripts (e.g. Π or R) denote non-stochastic steady state values.

(5) defines λ_t, the shadow value on the flow budget constraint facing a household. The parameter b measures internal habit formation and β is a discount factor. (6) is the Euler equation for bonds, which prices the gross nominal interest rate, R_t. (7) is the first order condition for capital utilization. The cost of capital utilization is a resource cost. (8) is the first order condition for effort and (9) is the optimal condition for hours; together these imply that effort is perfectly correlated with hours. (10) is the first order condition for investment; one can interpret the ratio of multipliers on the budget and capital accumulation constraints as Tobin's q_t, i.e. $q_t = \xi_t/\lambda_t$. (11) is the Euler equation for capital. The optimal condition for employment is (12). The household's stochastic discount factor is defined in (13). (14)-(16) describe optimal wage-setting by labor unions. $1 - \theta_w$ is the probability a wage can be adjusted in any period, and ϵ_w is the elasticity of substitution across different unions' labor. Non-updated wages can be fully indexed to trend output growth, g_Y. They are indexed to lagged inflation via the parameter $\gamma_w \in [0, 1]$ and to trend inflation, Π, via $1 - \gamma_w$.

Cost-minimization by firms gives rise to factor demand curves for capital and labor in (17)-(18). α is the exponent on capital services in the production function, with $1 - \alpha$ the exponent on labor. Because firms face the same factor prices, they all have the same real marginal cost and hire capital and labor in the same ratio. Each period, firms face a $1 - \theta_p$ probability of being able to adjust their price. Optimal price-setting for updating firms is characterized by (19)-(21). ϵ_p measures the extent of monopoly power in price-setting. ζ_p is a parameter measuring how much non-updated prices are indexed to lagged inflation; otherwise prices are indexed to trend inflation via $1 - \gamma_p$. The aggregate production function is given by (22). F is a fixed cost of production, scaled by X_t, which measures the economy's trend growth. v_t^p is a measure of price dispersion, the evolution of which is given by (23).

Physical capital accumulates according to the law of motion given in (24). The relationship between labor services supply and demand is given by (25); (26) describes the evolution of wage dispersion. The aggregate resource constraint is given by (27). There are physical resource costs to adjusting physical units of labor, physical units of capital, and capital intensity. The evolution of inflation and the aggregate real wage are governed by (30) and (31), respectively. Monetary policy is governed by a Taylor rule, (32). The exogenous processes for the marginal efficiency of investment shock, the intertemporal preference shock, and the stationary technology shock are given by (33)-(35). Each follows a stationary AR(1) process with steady state levels normalized to unity. The permanent productivity process is a stationary AR(1) in the growth rate and is given by (36). g denotes the steady state growth rate. The innovation is dated $t-q$, for $q \geq 0$. $q = 0$ means that the technology improvement materializes immediately. $q > 0$ means that agents observe the shock before it impacts productivity. Composite technology is the product of the stationary and non-stationary terms, given in (37).

Many of the variables in the model inherit the stochastic trend from Γ_t. It is straightforward to show that the stochastic trend factor is $X_t = \Gamma_t^{\frac{1}{1-\alpha}}$. Re-scaling trending variables by this factor renders the model stationary, and permits solution of the model using standard techniques. We solve the model via linearization about the non-stochastic steady state in the re-scaled variables. The steady state gross growth rate of output is $g_Y = g^{\frac{1}{1-\alpha}}$.

Labor's share is calculate as $\omega_{L,t} = \frac{w_t^l L_{s,t}}{Y}$. Traditional and adjusted TFP are calculated exactly as in Fernald:

$$\ln TFP_t - \ln TFP_{t-1} = (1-\omega_{L,t})(\ln K_t - \ln K_{t-1}) + \omega_{L,t}(\ln h_t + \ln N_t - \ln h_{t-1} - \ln N_{t-1}) \tag{38}$$

True factor utilization is:

$$\ln u_t - \ln u_{t-1} = \alpha(\ln z_t - \ln z_{t-1}) + (1-\alpha)(\ln e_t - \ln e_{t-1}) \tag{39}$$

Measured factor utilization is:

$$\ln \widehat{u}_t - \ln \widehat{u}_{t-1} = \widehat{\beta}(\ln h_t - \ln h_{t-1}) \tag{40}$$

Adjusted TFP is then:

$$\ln TFP_t^u - \ln TFP_{t-1}^u = \ln TFP_t - \ln TFP_{t-1} - (\ln \widehat{u}_t - \ln \widehat{u}_{t-1}) \tag{41}$$

The parameters of the model are set to values listed in Table 4 below:

Table 4: Calibrated Parameters

Description	Parameter	Value
Discount factor	β	0.99
Capital's share	α	1/3
Depreciation	δ	0.025
Capital use linear term	γ_1	0.04
Capital use squared term	γ_2	0.01
Steady state gross inflation	Π	1
TR inflation	ϕ_π	1.5
TR output growth	ϕ_y	0.5
TR smoothing	ρ_R	0.8
Elasticity sub goods	ϵ_p	11
Elasticity sub labor	ϵ_w	11
Labor scaling	θ	4.19
$G(\cdot)$ constant	κ_0	0.06
$G(\cdot)$ linear hours	κ_1	243
$G(\cdot)$ squared hours	κ_2	6
$G(\cdot)$ linear effort	κ_3	0.30
$G(\cdot)$ squared effort	κ_4	1.50
Fixed cost	F	0.25
Calvo prices	θ_p	0.75
Calvo wages	θ_w	0.9
Price indexation	γ_p	0.00
Wage indexation	γ_w	1
Habit formation	b	0.8
Investment adjustment cost	φ	2
Labor adjustment cost	ψ	2
SS growth of productivity	g	1.0033
AR productivity growth	ρ_Γ	0.70
AR stationary productivity	ρ_S	0.90
AR investment	ρ_μ	0.80
AR intertemporal preference	ρ_ν	0.90
SD growth shock	$100\sigma_g$	0.2225
SD stationary productivity	$100\sigma_S$	0.0445
SD investment shock	$100\sigma_\mu$	0.4450
SD monetary shock	$100\sigma_R$	0.0445
SD preference shock	$100\sigma_\nu$	4.4500

These parameter values are largely drawn from the literature and are therefore quite standard, with a few exceptions. As noted in the text, we assume a somewhat higher degree of wage rigidity than is standard. The fixed cost of production, F, is chosen so that profits are zero in steady state or the fixed cost is set to 0 and the linear term in the utilization adjustment cost is set to normalize steady state capital utilization to unity. The unit of time, T, is set to one. The scaling parameter on the disutility from labor is set to normalize total physical labor input of $N = 3/5$, which is in-line with labor force participation data. The parameters of the $G(\cdot)$ function are set as follows. We normalize steady state hours to $h = 1/3$ and target a steady state value of the function also equal to $1/3$. We target a Frisch elasticity of average hours of 1. We then target an elasticity of effort with respect to hours of 4. Altogether, these targets and normalizations pin down κ_j for $j = 0, \ldots, 4$.

Our model features five stochastic shocks. We set the autoregressive parameters in the shock processes to conventional values. With the shock standard deviations calibrated as they are, the model generates a standard deviation of output growth of 1 percent, with the intertemporal preferenc shock accounting for 40 percent of the unconditional variance of output growth, the investment shock 25 percent, the news shock 28 percent, the surprise technology shock 6 percent, and the monetary policy shock less than 1 percent.

4 Robustness of max-share identification to alternative measures of productivity

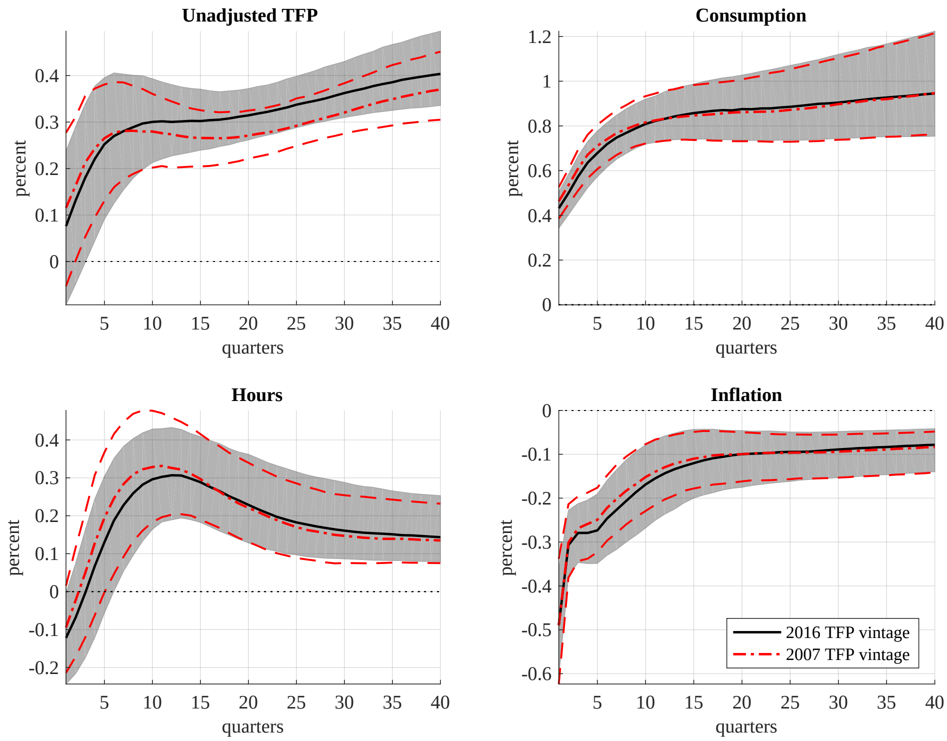
In this section we re-estimate the baseline four-variable VAR replacing the utilization-adjusted measure of TFP with either unadjusted TFP or average labor productivity. We then apply the max-share identification to these systems to check for robustness of our results.

Figure 3 reports the impulse responses to the max-share shock when unadjusted TFP is used in the VAR. The results are essentially the same for both the 2007 and the 2016 vintages, confirming that revisions in the different components of (unadjusted) TFP do not affect the results. The responses of the different variables also look very similar to the ones reported in the main text based on the VAR with adjusted TFP, thus confirming the robustness of the max-share identification. The only difference is the short-run response of unadjusted TFP, due to the fact it is not corrected for utilization. Specifically, as defined in the main text,

$$\ln TFP_t^u = \ln TFP_t - \ln \hat{u}_t.$$

Estimated utilization declines slightly on impact and then increases in a humpshaped pattern before gradually returning to zero. Hence, unadjusted TFP responds less on impact than adjusted TFP but then increases as a faster pace before leveling out at approximately the same permanently higher long-run level.

Figure 3: Max-share identification with unadjusted TFP

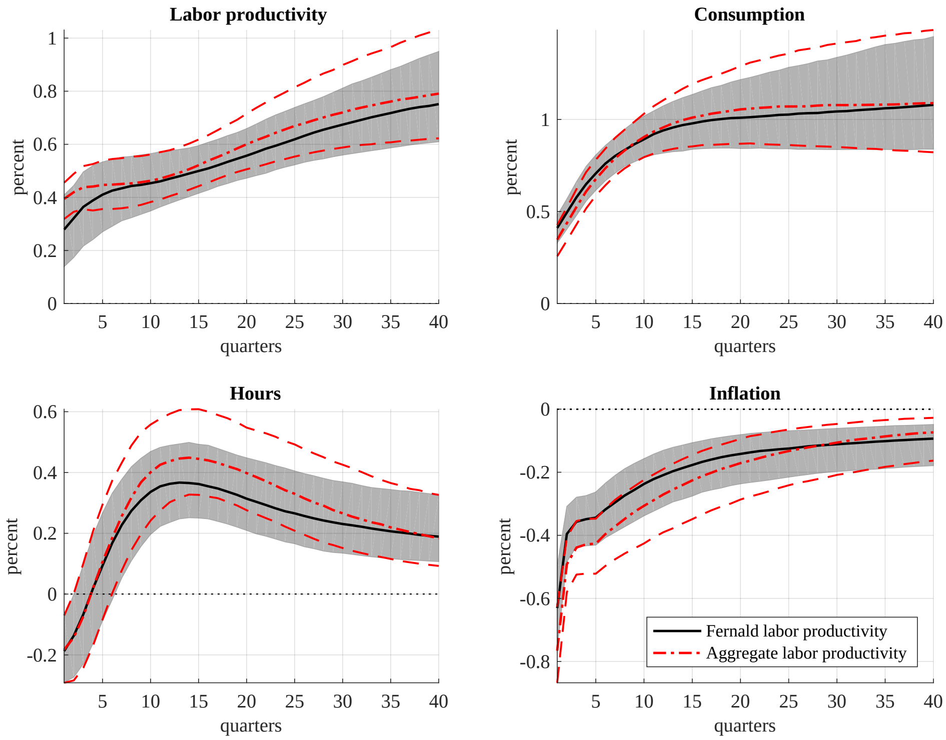


Notes: Solid black lines are the posterior median estimates from the eight variable VAR system estimated with the 2016 vintage of adjusted TFP. The gray bands correspond to the 16 to 84 percent posterior coverage intervals. The red dash-dotted lines are the posterior median estimates for the system estimated with average labor productivity, defined as output per hour worked in the non-farm business sector. The red dashed lines correspond to the 16 to 84 percent posterior coverage intervals.

Figure 4 reports the impulse responses to the max-share shock when labor productivity is used in the VAR. Labor productivity is measured either as real GDP divided by total non-farm business hours or as in Fernald (2014) as the ratio of business output to quality-adjusted total business hours.[1] The results are very similar for the two measures and the responses for consumption, total hours and inflation match very closely the responses obtained with adjusted TFP in the main text, again confirming the robustness of the max-share approach.

[1]Business output is the equally weighted average of expenditure-based and income-based real output. The quality adjustment for hours is based on wage regressions by Aaronson and Sullivan (2001) and BLS multifactor productivity data. See Fernald (2014) for details.

Figure 4: Max-share identification with labor productivity



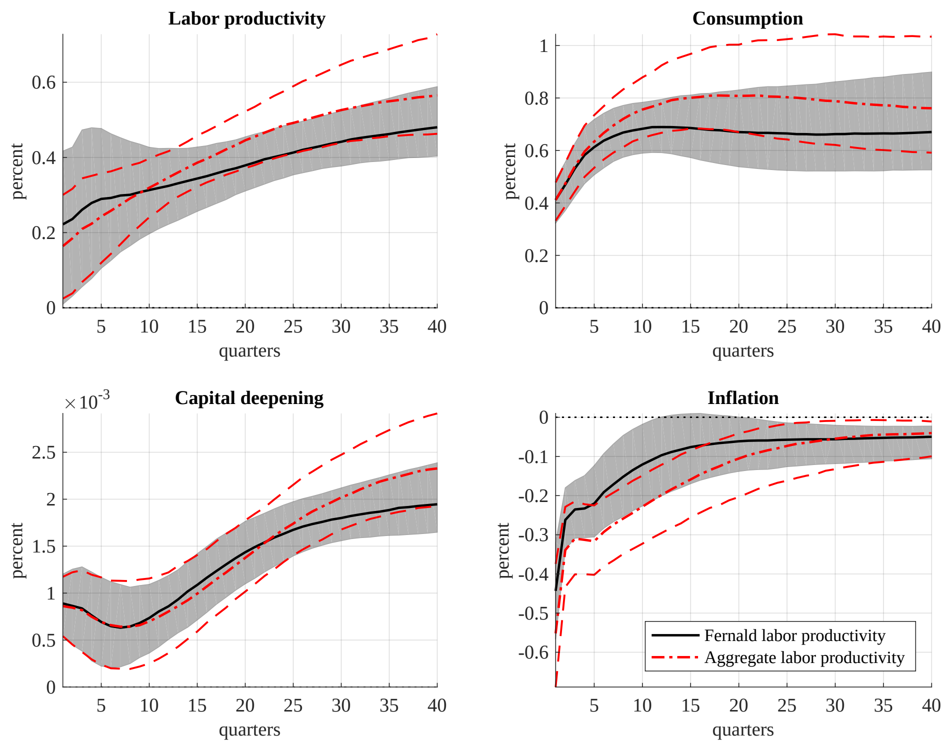
Notes: Solid black lines are the posterior median estimates from the four variable VAR system estimated with the 2016 vintage of adjusted TFP. The gray bands correspond to the 16 to 84 percent posterior coverage intervals. The red dash-dotted lines are the posterior median estimates for the system estimated with average labor productivity, defined as output per hour worked in the non-farm business sector. The red dashed lines correspond to the 16 to 84 percent posterior coverage intervals.

The only difference is that labor productivity jumps up significantly on impact and then gradually increases to a permanently higher level that is about twice as high as for adjusted TFP. The reason for this difference is capital deepening; i.e.

$$\ln Y_t - \ln L_t = \ln TFP_t - \ln \hat{u}_t + (1 - \omega_{L,t})(\ln K_t - \ln L_t).$$

On impact, hours decline and capital barely responds. In the long-run, the hours response returns to zero whereas capital increases permanently. So, there is capital deepening both in the short- and the long-run, explaining the larger response of labor productivity relative to adjusted TFP (of course, in the short run, there are also variations in utilization that drive a wedge between adjusted TFP and labor productivity). This is shown in Figure 5 where we replaced total hours with capital intensity (the difference between capital stock and quality adjusted total hours, both from Fernald's data).

Figure 5: Max-share identification with labor productivity

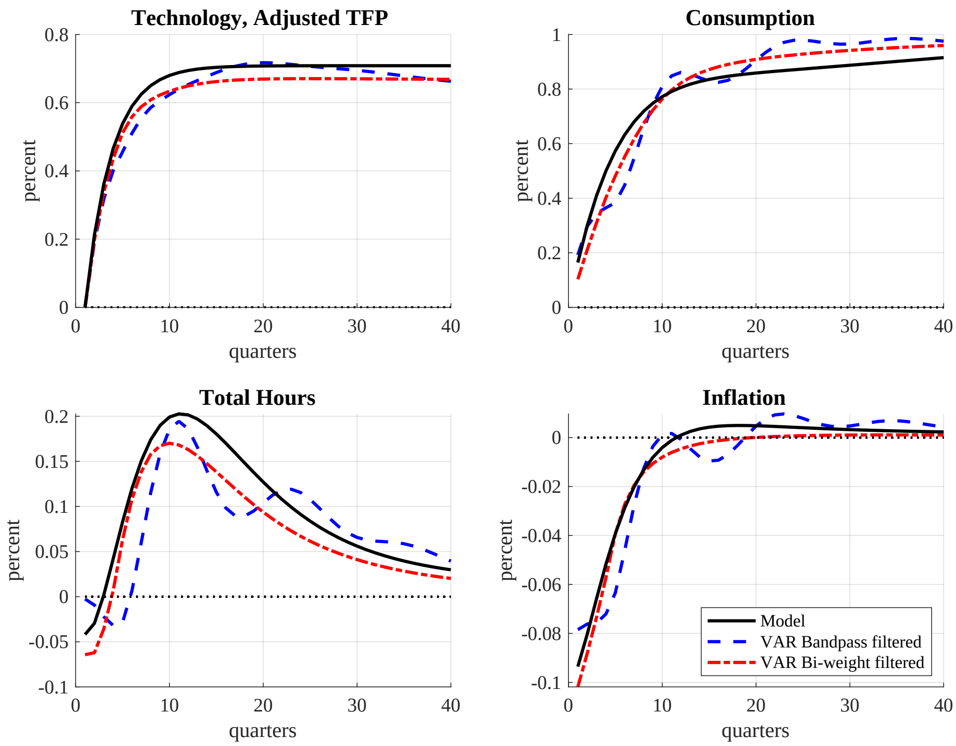


Notes: Solid black lines are the posterior median estimates from the four variable VAR system estimated with the 2016 vintage of adjusted TFP. The gray bands correspond to the 16 to 84 percent posterior coverage intervals. The red dash-dotted lines are the posterior median estimates for the system estimated with average labor productivity, defined as output per hour worked in the non-farm business sector. The red dashed lines correspond to the 16 to 84 percent posterior coverage intervals.

5 Additional Monte-Carlo simulation results for max-share identification

In the main text, we only report Monte-Carlo results for the max-share identication when the proportionality condition fails to hold. Here we also show results for the case when the proportionality condition holds; i.e. capital use is constant ($\sigma_z = 0$) and $\widehat{\beta}$ is exactly correct. This is shown in Figure 6. Similarly to the Barsky-Sims identication for the case of when the proportionality condition holds, the max-share identication performs well at replicating the model's impulse responses regardless of filtering method.

Figure 6: Simulated Responses to Max-Share Shock when Proportionality Holds



Notes: Solid lines are the true impulse responses to a news shock in the model. The dashed blue lines are the estimated responses using the max-share identification based on the simulated data with bandpass filtered hours per worker in the construction of utilization. The dash-dotted red lines are the estimated responses using the max-share identification based on the simulated data with bi-weight filtered hours per worker in the construction of utilization.

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