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Productivity, energy prices and the great moderation: A new link ☆

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ABSTRACT

We build upon recent research that attributes the moderation of output volatility since the 1980s to the reduced volatility of the Total Factor Productivity (TFP) by investigating the linkage between energy price fluctuations and the stochastic process for TFP. First, we estimate a joint stochastic process for the energy price and TFP and establish that until around 1982, energy prices negatively affected TFP. This spillover has since disappeared. Second, we show that within the framework of a Dynamic Stochastic General Equilibrium (DSGE) model, the disappearance of this energy-productivity spillover accounts for close to 68 percent of the moderation in output volatility.

1. Introduction

The volatility of output in the United States has declined significantly since the mid 1980s, as first documented by Kim and Nelson (1999) and McConnell and Perez-Quiros (2000).[3] This drop in volatility is an artifact economists also call the "Great Moderation." While there is some disagreement on what types of shocks are responsible for the drop in volatility—for instance, Fernandez-Villaverde and Rubio-Ramirez (2007) or Justiniano and Primiceri (2008) emphasize the role of shocks to the price of investment goods—a good starting point is to investigate the reduced volatility of Total Factor Productivity, which according to Arias et al. (2007) or Leduc and Sill (2007), plays an important role in the reduction of macroeconomic instability.[4] This raises the question: what caused the moderation of TFP volatility in the 1980s? We investigate the link between energy price fluctuations and the TFP stochastic process in the 1980s, which we term as a "spillover." We find a

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[3] Stock and Watson (2002) also document the fall in volatility in other important macro variables such as consumption, investment, and hours worked.
[4] Arias et al. (2007) have ruled out previously conjectured channels such as unmeasured factor utilization in the construction of the TFP, government spending shocks and preference shocks as the source of output volatility moderation. Leduc and Sill (2007) show that a change in monetary policy can

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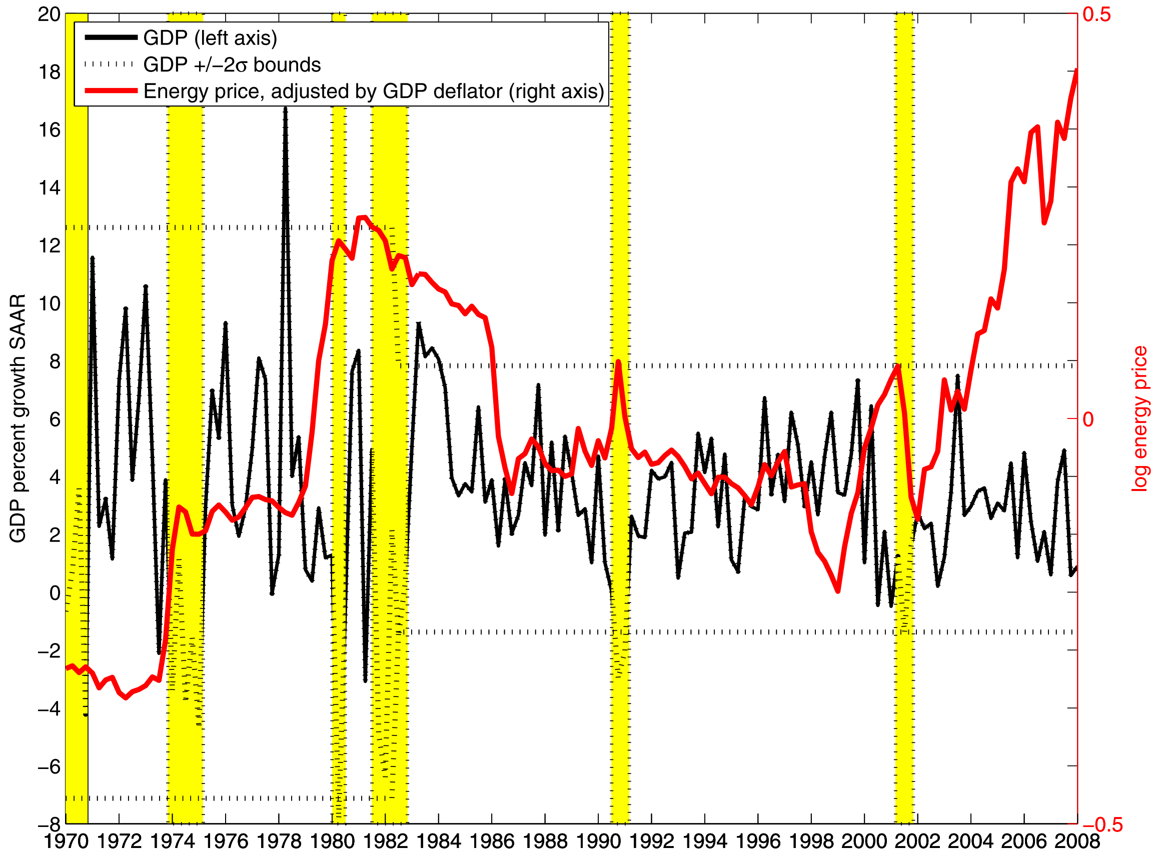

Fig. 1. GDP growth (black, left axis) and (log) real energy prices (red, right axis) with NBER-dated recession (shaded regions). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

new stylized fact that the drop in TFP volatility has to do with the disappearance of this spillover from energy price shocks to TFP after 1982.

Why would the fluctuations in energy prices be important for the Great Moderation? Looking at the energy price and its relationship with business cycles in Fig. 1 reveals that the deep recessions in 1973–1974 and 1980–1982 were preceded by large energy price spikes.[5] However, the sharp energy price drop in 1986 did not spark a significant acceleration in GDP growth. Also, note that the current recession is most likely a result of the ongoing severe credit market disruptions that started in August 2007, rather than the energy price hike between 2002 and the summer of 2008.[6] Our hypothesis from these observations is that a link between energy prices and business cycles existed in the early period, say, before 1982, but has since disappeared, potentially accounting for the lower volatility of macro variables.

Hence, in our empirical analysis we estimate a joint stochastic process for quarterly energy prices and TFP using Bayesian estimation methods. We explicitly model a spillover effect from the energy price innovations to TFP and the magnitude of this spillover varies over time. Specifically, we allow for a breakpoint from one regime into another, and the timing of this break itself is a parameter to be estimated. We find the second quarter of 1982 (1982:II) to be the estimated breakpoint. Before 1982:II, innovations in the process for the energy price had a significant and negative spillover into TFP. This spillover disappeared afterwards. This result is in similar vein as that of Hooker (1996, 1999) and Davis and Haltiwanger (2001) who have noted that the statistical relationship between oil prices and output weakened in the mid-1980s. Recently, Herrera and Pesavento (2009), also found that energy prices had a larger effect on output and inflation in the pre-Volcker era. We are silent about the origin of the spillover in the early regime or its disappearance during the second regime. We conjecture that a possible reason for the larger amplification of oil shocks in the 1970s was the existence of price controls during the Nixon and Carter years.

Next, we use a dynamic stochastic general equilibrium (DSGE) modeling framework to evaluate the impact of the changing nature of the joint stochastic process for energy prices and TFP on key macro volatilities. We take a model similar to

account for lower inflation volatility but not the drop in output volatility. In addition, oil price shocks cannot account for the drop in output volatility. For additional explanations in the Great Moderation debate see the survey by Owyang et al. (2007).

[5] See Hamilton (1983, 2003) and Hamilton and Herrera (2004) for evidence on the link between energy prices and business cycles. This link, however, has been challenged in recent research by Barsky and Kilian (2002; 2004). See Kilian (2008b) and Hamilton (2008) for a detailed survey on the link or lack thereof between energy prices and the macroeconomy.

[6] Incidentally, the large deterioration of economic conditions occurred in the fourth quarter of 2008, when the energy price had already dropped significantly from its peak in July.

Kim and Loungani (1992), which incorporates energy use as a complement to fixed capital on the production side, and simulate it with the pre- and post-1982:II specification for the joint stochastic process for the price of energy and TFP. We show that the absence of the spillover effect after 1982:II reduces output volatility by about 34 percent.[7] Given that the actual drop in output volatility after 1982 was about 55 percent, the changing nature of the stochastic process accounts for about 61 percent of the Great Moderation in output volatility. Our results point to a "structural change" as the origin of the Great Moderation, relative to the "good luck" explanation, and are therefore consistent with findings by Galí and Gambetti (2007). Our analysis is similar in spirit to Backus and Crucini (2000) who found that including oil and accounting for the changing composition of shocks hitting the economy explains the apparent break in the correlation between terms of trade and output in the data. Finally, our results show that the noticeable break in the volatility of TFP can be explained by a change in the relationship between energy prices and TFP, and not because of a lower variance of the innovations to TFP.

One can object that the significant drop in the share of energy use in GDP since the early 80's can directly account for the reduced volatility, without the added link of energy spillover on productivity. Thus, we simulate the model without an energy-productivity spillover but with different energy shares calibrated to the observed energy-to-output ratios in the pre- and post-1982:II time periods. This experiment generates a drop in output volatility of only 5 percent, compared to the 54 percent observed in the data. Thus, a drop in the energy share accounts for a marginal proportion (less than 10 percent) of the Great Moderation. Of course, if we simulate the model not only with different stochastic processes but also with different energy shares calibrated to the early and late period, we enhance the drop in output volatility to 40 percent, bringing the share of the Great Moderation accounted for energy-related changes to 73 percent.

Our paper proceeds as follows. Section 2 details the specification and estimation of the joint stochastic process for TFP and energy. Section 3 introduces the DSGE model and the calibration of the remaining parameters. Section 4 presents the simulation results in the benchmark case with fixed energy shares, and for the model with varying energy shares. Finally, Section 5 concludes our paper.

2. Econometric setup

This section describes the reduced form models that are fit to the series of energy prices and TFP and which are the forcing processes in the DSGE model presented below. We exponentially detrend both the energy prices and TFP series prior to estimation. As in Kim and Loungani (1992) and Dhawan and Jeske (2008), we model the energy price time series as an ARMA(1,1) process,

$$p_t = \rho^p p_{t-1} + \epsilon_t^p + \xi \epsilon_{t-1}^p \tag{1}$$

To justify this specification, we have computed the Akaike Information Criterion (AIC) for the ARMA(1,1) and for a set of alternative specifications and found the ARMA(1,1) to have the best fit. Specifically, the AIC differences between our ARMA(1,1) and AR(1), AR(2), ARMA(1,2), ARMA(2,1) and ARMA(2,2) were 14.4834, 2.3290, 1.4322, 0.9892, and 2.7219, respectively.

The ϵ_t^p is a zero-mean innovation to the energy price shock assumed to be normally distributed with a variance σ_p^2. We assume that oil price movements are strictly exogenous, which is the conventional view in the literature as they are often attributed to political developments in the Middle East (see, e.g., Bernanke et al., 1997).[8]

We deviate from the usual AR(1) specification for the productivity process, as the innovation in our study is to assume spillover effects from energy prices into TFP. As a result, we specify a process in which productivity z depends on past values of innovations to the energy prices,

$$z_t = \rho^z z_{t-1} + \epsilon_t^z + \sum_{\tau=1}^{4} \gamma_t^\tau \epsilon_{t-\tau}^p \tag{3}$$

The degree (and direction) of the spillover will be given by the values of γ_t^τ. Note the subscript t in the spillover parameter γ: we assume that the degree of spillover effects from energy prices to productivity has changed in the last four decades. Specifically, we model this as a one-time change with an unknown date t^*, which we will treat as another parameter to be estimated. As a consequence, the spillover parameters will take on values $\gamma_1 = (\gamma_1^1, \gamma_1^2, \gamma_1^3, \gamma_1^4)$ in the first part of the sample and $\gamma_2 = (\gamma_2^1, \gamma_2^2, \gamma_2^3, \gamma_2^4)$ in the second part. This means the productivity process has the following form

$$z_t = \rho^z z_{t-1} + \epsilon_t^z + \sum_{\tau=1}^{4} \gamma_t^\tau \epsilon_{t-\tau}^p, \quad \epsilon_t^z \sim N\big(0, \sigma_{z,t}^2\big) \tag{4}$$

[7] Consumption and investment volatilities also declined by a similar magnitude.

[8] However, some recent papers (Barsky and Kilian, 2002; Kilian, 2008a and Kilian, 2009) have challenged this full exogeneity view. Consequently, we have also experimented with a specification for oil prices that allows for feed-back effects from TFP into oil prices. Specifically we fitted,

$$p_t = \rho^p p_{t-1} + \rho^{p,z} z_{t-1} + \epsilon_t^p + \xi \epsilon_{t-1}^p \tag{2}$$

where the coefficient $\rho^{p,z}$ reflects the effect of TFP into oil prices. Our estimates imply a value for $\rho^{p,z}$ that is small and insignificant. Using this estimated $\rho^{p,z}$ value yielded very similar results in our DSGE model simulations (results available upon request).

where

$$\gamma_t = \left(\gamma_t^1, \gamma_t^2, \gamma_t^3, \gamma_t^4\right) = \begin{cases} \gamma_1 & \text{if } t \leqslant t^* \\ \gamma_2 & \text{if } t > t^* \end{cases} \tag{5}$$

and

$$\sigma_{z,t}^2 = \begin{cases} \sigma_{z,1}^2 & \text{if } t \leqslant t^* \\ \sigma_{z,2}^2 & \text{if } t > t^* \end{cases} \tag{6}$$

The reader should note that we have also allowed for a time-varying variance of the TFP innovations, reflected in the t subscript in $\sigma_{z,t}^2$. It is conceivable that failing to take into account the drop in the volatility of innovations could result in over-stating the effect of the change in the spillover term across the two regimes. The reason is that we would force the estimation to assign a bigger role in the spillover term in the drop in the variance of TFP.

We use data for quarterly energy price and productivity $\{p_t, z_t\}_{t=1}^T$ to estimate the parameters of the two stochastic processes, where T is the sample size. Data cover the period from 1970 to 2005. Appendix B has the details on how we construct the quarterly series for TFP and the energy price.

We model the one-time change in γ and σ_z^2 as the transition of a two-state Markov process into an absorbing state. Assume that the value of γ and σ_z^2 is driven by a latent variable S_t, $S_t \in \{0, 1\}$ for any t, which follows a Markov chain with transition probability:

$$\Pi_\epsilon = \begin{bmatrix} q & 1-q \\ 0 & 1 \end{bmatrix} \tag{7}$$

We let the data inform us whether there has been a transition into a state in which $S_t = 1$. If a transition occurs, we denote the date at which occurs as t^*. The goal of the procedure is to estimate the vector of parameters and latent variables: $\{\rho^p, \xi, \sigma_p^2, \rho^z, \gamma_1, \gamma_2, \sigma_{z,1}^2, \sigma_{z,2}^2, \{S_t\}_{t=1}^T, q, t^*\}$.

The procedure can be split into two steps: the estimation of the energy price process and the estimation of the productivity process.

In the energy price process there is a total of three parameters to estimate. Denote the vector of the three parameters $\theta_p = \{\rho^p, \xi, \sigma_p\}$ and $f_p(\theta_p)$ the prior distribution over these parameters. To construct the likelihood function we first cast the ARMA(1,1) as a state-space system:

$$\zeta_{t+1} = \begin{bmatrix} \rho^p & 0 \\ 1 & 0 \end{bmatrix} \zeta_t + w_{t+1} \tag{8}$$

$$p_t = [1 \quad \xi\,]\zeta_t + v_{t+1} \tag{9}$$

The likelihood, $L(\{p_t\}_{t=1}^T | \theta_p)$ is then constructed as described in Hamilton (1994, Chapter 13, p. 385), which makes use of the Kalman filter to integrate out the latent vector ζ_t. Once we compute the likelihood, we find the posterior distribution, $p(\theta_p | \{p_t\}_{t=1}^T)$, by coupling the likelihood and the prior: $f_p(\theta_p | \{p_t\}_{t=1}^T) \propto L(\{p_t\}_{t=1}^T | \theta_p) f_p(\theta_p)$.

Next we estimate the productivity process using the a time series of $\{\epsilon_t^p\}_{t=1}^T$ as data. Denote by θ_z the vector of parameters $\{\rho_z, \gamma_1, \gamma_2, \sigma_{z,1}, \sigma_{z,2}, q\}$. First, we endow θ_z with a prior distribution $f_z(\theta_z)$. In computing the likelihood for the TFP process, an obvious difficulty is that the vector $\{S_t\}_{t=1}^T$ is not observed. If it were observed, the likelihood function would be:

$$L\left(\{z_t\}_{t=1}^T | \theta_z, \{S_t\}_{t=1}^T\right) = \prod_{t=5}^T \frac{1}{\sqrt{2\pi\sigma_z^2}} \exp\left\{-\frac{1}{2\sigma_z^2} e_t^2\right\} \tag{10}$$

with $e_t = z_t - \rho_z z_{t-1} - \sum_{\tau=1}^4 \gamma_1^\tau \epsilon_{t-\tau}^p$ for $S_t = 0$ and $e_t = z_t - \rho_z z_{t-1} - \sum_{\tau=1}^4 \gamma_2^\tau \epsilon_{t-\tau}^p$ for $S_t = 1$. Given that we do not know $\{S_t\}_{t=1}^T$, we use a filtering (and smoothing) procedure similar to that described in Kim and Nelson (1999, Chapters 4 and 9). In a technical appendix we provide a brief step-by-step description of our sampling procedure.

We report the prior distribution for the parameters in Table 1. We have used truncated Normal distributions[9] for ρ^p, ρ^z, ξ, γ_1, and γ_2; Gamma distributions for σ_p^2, $\sigma_{z,1}^2$, and $\sigma_{z,2}^2$; and a Beta distribution for q. These distributions are fairly uninformative except for the sign restriction in the γ's to be able to identify the two regimes. The prior distribution for q implies a mean of 0.50 and a standard deviation of 0.48 and the prior distribution for the variances of the shocks has a low mean (9.35×10^{-5}) but a large standard deviation (0.009). Table 2 shows our estimation results. We date the time of the change at the second quarter of 1982, but this being an estimate, there is some uncertainty around it as well. A 90% posterior region is bounded by the third quarter of 1979 and the second quarter of 1985. In the first subperiod the spillover

[9] We have used indicator variables to determine the region of truncation. For example $\chi_{|\rho^p|<1}$ takes the value of zero whenever the absolute value of ρ_p is greater than one.

Table 1
Prior distributions.

Parameter	Distribution
ρ^p	$N(0.9, 1.5^2)\chi_{\lvert\rho^p\rvert<1}$
ξ	$N(0, 0.4^2)$
σ_p^2	$Gamma(0.0001, 1)$
ρ^z	$N(0.9, 1.5^2)\chi_{\lvert\rho^z\rvert<1}$
$\{\gamma_1^i\}_{i=1}^4$	$N(0, 0.15^2)\chi_{\gamma_1^i>0}$
$\{\gamma_2^i\}_{i=1}^4$	$N(0, 0.15^2)\chi_{\gamma_2^i<0}$
$\sigma_{z,1}^2$	$Gamma(0.0001, 1)$
$\sigma_{z,2}^2$	$Gamma(0.0001, 1)\chi_{\sigma_{z,2}^2<\sigma_{z,1}^2}$
q	$Beta(0.6, 0.4)$

Table 2
Estimation results.

Parameter	Posterior mean	Post. std. dev.
ρ^p	0.921	0.040
ξ	0.375	0.102
σ_p^2	0.001	1.59×10^{-4}
ρ^z	0.912	0.029
γ_1	$[-0.092, -0.026, -0.067, -0.046]$	$[0.040, 0.021, 0.035, 0.029]$
γ_2	$[0.015, 0.021, 0.027, 0.011]$	$[0.010, 0.011, 0.013, 0.008]$
$\sigma_{z,1}^2$	5.45×10^{-5}	1.21×10^{-5}
$\sigma_{z,2}^2$	2.08×10^{-5}	3.09×10^{-6}
q	0.966	0.026
t^*	1982:III	[1982:II, 1983:II]

Table 3
TFP variance decomposition: spillover vs. innovations.

	TFP variance	% of variance	% of absolute var. drop
Total (Regime 1)	7.38×10^{-4}	100%	N/A
Due to spillover	3.78×10^{-4}	51%	N/A
Due to innovations	3.61×10^{-4}	49%	N/A
Total (Regime 2)	1.79×10^{-4}	100%	100%
Due to spillover	4.01×10^{-5}	22%	61%
Due to innovations	1.39×10^{-4}	78%	39%

parameters γ are significantly less than zero. For the second subperiod, however, zero is well within two posterior standard deviations of the mean, so we can conclude that the spillover effect is only significant during the first period (i.e. the period for which $t < t^*$), in which higher energy prices due to positive innovations affect TFP negatively. As is expected the parameters driving persistence in energy prices and TFP are large, while the variance of the innovations to TFP drops to half its value during the second regime. The innovations to energy prices have a much larger variance relative to those of TFP.

How much does each of the two factors—the drop in the variance of innovations and the disappearance of the energy price spillover—account for the decline in the variance of TFP? We report this decomposition in Table 3. The first two columns of that table report the variance of TFP across the two regimes, and the level and percentage of this variance attributed to each of the two factors. During Regime 1—the high volatility regime—each factor accounts for roughly half of the overall variance (51% for the energy price spillover); during Regime 2, the fraction of the variance attributed to the spillover drops to about 22%. As a result, the drop in the variance across the two regimes is mostly due to the decrease in the spill over effect, explaining about 61% of the total drop in volatility. Visually, this effect is shown in Fig. 2 which displays actual HP-detrended TFP for our sample—represented by the solid line—and a *counterfactual* TFP, also HP-detrended,[10] constructed by assuming no spillover effect from energy prices into TFP during either regime. The results displayed in Table 3 are apparent from the figure. Up to 1982—Regime 1—the two lines are rather different as the spillover effect is strong and its contribution to the variance is high. During Regime 2, the spillover parameters are closer to zero, reducing their contribution to the overall variance of TFP and increasing the similarity between the solid and the dotted lines.[11]

One might be tempted to interpret our results as picking up changes in correlations between average growth rates of the two variables. In other words, the 1970s were characterized by low mean productivity growth and high oil prices. Mean

[10] The smoothing parameter of the HP filter is 1600, the same number used in the DSGE section below.

[11] It is also apparent from the plot that the spillover effect made the 1975 recession much worse. Interestingly, the recovery between the 1980 and 1982 recessions would have been stronger had there been no spillover effect present.

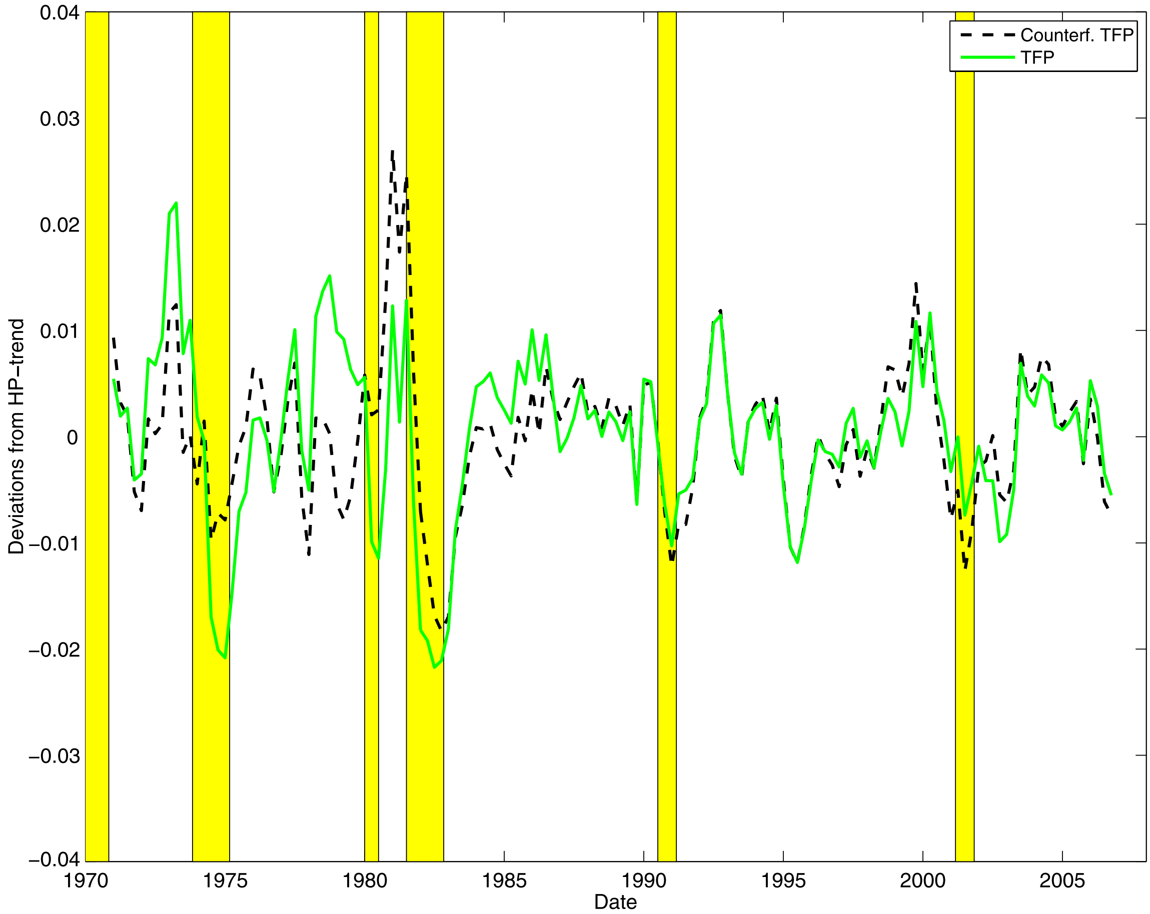

Fig. 2. Actual deviations of TFP from and HP-trend (solid line) and a counterfactual TFP assuming no spillover effects from energy prices (dotted line). Also shown are NBER-dated recessions (shaded regions).

productivity growth increased in the 1980s, coinciding with a smaller average growth rate of oil prices. If one exponentially detrends the data prior to estimation, as we have done, one retains significant volatility at frequencies lower than the ones related to "business cycles." To ensure that our results were not driven by those mean changes we conducted the empirical analysis with two different detrending procedures. First, we assumed that trend-growth in productivity was lower in the 1970s than in the remainder of the sample, resulting in mean-zero deviations from trend pre- and post-1980. Second, we HP-filtered both oil prices and TFP, therefore eliminating variation at even lower frequencies. The parameters reflecting the spillover and the timing of the structural change were similar in all three cases.[12]

3. Model

In the previous section we showed that there is a statistically significant difference between the parameters of the TFP process in the two subperiods. How significant are the two different shock processes for TFP in an economic sense? To answer this question we feed the stochastic process for the energy price and the two alternative specifications for the productivity process into a DSGE model. The model is very similar to the one described in Kim and Loungani (1992). Households have preferences over consumption c and leisure equal to the normalized total hours less hours worked h,

$$U = E_0 \sum_{t=0}^{\infty} \beta^t \left[\varphi \log c_t + (1-\varphi)\log(1-h_t)\right] \tag{11}$$

Output y is produced by a representative firm that combines hours, capital stock k and energy e. Production is also subject to a stochastic total productivity shock z,

$$y_t = z_t \left(\eta k_{t-1}^{\nu} + (1-\eta) e_t^{\nu}\right)^{\alpha/\nu} h_t^{1-\alpha} \tag{12}$$

[12] Results for this modification are available upon request.

Table 4
Model parameters.

Parameter	Value
β	0.9900
α	0.3600
ν	−0.7000
φ	0.3376
η	0.9959
δ	0.0154

The elasticity of substitution between capital and energy is $\frac{1}{1-\nu}$. Consequently, the production function displays complementarity between capital and energy when $\nu < 0$.[13] Energy has to be imported at the relative price p_t and capital depreciates at a rate δ, thus the economy's resource constraint is

$$c_t + k_t - (1-\delta)k_{t-1} + p_t e_t = y_t \tag{13}$$

and the capital stock evolves according to

$$k_t = (1-\delta)k_{t-1} + i_t$$

The social planner thus solves the following optimization problem

$$\max E_0 \sum_{t=0}^{\infty} \beta^t \big[\varphi \log c_t + (1-\varphi)\log(1-h_t)\big] \tag{SP}$$

subject to

$$c_t + k_t - (1-\delta)k_{t-1} + p_t e_t = z_t \big(\eta k_{t-1}^{\nu} + (1-\eta)e_t^{\nu}\big)^{\alpha/\nu} h_t^{1-\alpha} \tag{14}$$

and

$$p_t = \rho^p p_{t-1} + \epsilon_t^p + \xi \epsilon_{t-1}^p \tag{15}$$

$$z_t = \rho_z z_{t-1} + \epsilon_t^z + \sum_{\tau=1}^{4} \gamma^\tau \epsilon_{t-\tau}^p \tag{16}$$

We need to assign values for the following parameters: β, φ, α, ν, η, δ. Throughout the paper, we set the parameters α, β and ν at 0.36, 0.99, and −0.70 as in Kim and Loungani (1992).[14] We calibrate the remaining parameters to match the targets $k/y = 12$, $e/y = 0.0544$ and $h = 0.3$. We report the parameters from this calibration exercise in Table 4.[15]

4. Results

4.1. Benchmark

We solve the model by computing a log-linear approximation around the deterministic steady state. We do so for the two alternative sets of γ and σ_z^2 parameters in the stochastic process for TFP to simulate the economy under the two regimes.

In Table 5, we report the volatilities of output, consumption, investment and hours worked in the data and in the model in the two different periods (pre- and post-1982:II). Volatility in the data dropped across the board, by about 55 percent for output and consumption, 49 percent for fixed investment and 43 percent for hours worked. The table reports results for two different versions of the model. The "Baseline" model includes both the change in the spillover parameters and the change in the variance of innovations. These two factors generate roughly the entire drop in volatility: a 53% drop in output volatility, a 57% drop in that of output, and drops of 49% and 43% percent for investment and hours respectively.[16] We perform a second experiment and report its results on the columns labeled "Spillover Only." This second experiment entails

[13] An alternate route would be to have a putty–clay model as in Atkeson and Kehoe (1999) to allow for different short-run and long-run elasticities of substitution between energy and capital. Dhawan and Jeske (2008) have shown that this modeling structure has similar business cycle properties as the Kim and Loungani type structure used here.

[14] These authors used two values for ν: −0.7 and 0.001—which is equivalent to a Cobb–Douglas production function. We prefer −0.7 as a larger degree of complementarity is consistent with the time-series behavior of capital and energy use over the post-war period—see Polgreen and Silos (2009).

[15] See Dhawan et al. (2008) for the derivation of first order conditions and calibration details.

[16] Notice that the consumption volatility in the model is much lower than in the data. As we know from Cooley and Prescott (1995), DSGE models have a hard time generating enough consumption volatility.

Table 5
Volatility in the data versus model.

	Early period (1970:I–1982:I)			Late period (1982:II–2006:IV)			Percentage drop in volatility		
	Data	Baseline	Spillover only	Data	Baseline	Spillover only	Data	Baseline	Spillover only
Output	2.52	2.30	2.06	1.16	1.08	1.30	−54.03	−53.00	−36.96
Consumption	1.76	0.47	0.41	0.73	0.20	0.25	−58.55	−56.83	−38.88
Investment	7.12	11.07	10.12	3.63	5.28	6.26	−48.91	−52.30	−38.18
Hours	1.97	1.39	1.27	1.12	0.67	0.83	−43.27	−51.57	−34.83

Note: Volatilities refer to the standard deviation of log-deviations from HP-filtered series ($\lambda = 1600$).

Table 6
Different calibration targets for energy shares and corresponding parameter values.

	Early period (1970:I–1982:I)	Late period (1982:II–2006:IV)
e/y	0.0678	0.0436
η	0.9938	0.9973
δ	0.0142	0.0163

Table 7
Volatility in the data versus model: Different energy shares, no spillover.

	Early period (1970:I–1982:I)		Late period (1982:II–2006:IV)		Percentage drop in volatility	
	Data	Model	Data	Model	Data	Model
Output	2.52	1.32	1.16	1.26	−54.03	−4.42
Consumption	1.76	0.28	0.73	0.26	−58.55	−8.09
Investment	7.12	6.60	3.63	5.89	−48.91	−10.81
Hours	1.97	0.79	1.12	0.76	−43.27	−3.92

Note: Volatilities refer to the standard deviation of log-deviations from HP-filtered series ($\lambda = 1600$).

shutting off the drop in the variance of innovations to TFP to isolate the effect of the change in the degree of spillover. To do so, we set the variance of the innovations to TFP to its average value—weighted by the lengths of the two regimes—and change only the γ parameters. This change generates a drop in output volatility of almost 37 percent. Thus, 68 percent of the moderation is explained by a change in the spillover effect of energy price into TFP. Consumption, investment and hours volatility also drops by about 34 to 39 percent.

4.2. Different energy shares

The energy share in the production has diminished in the last decades, which can be another cause for the drop in output volatility. Thus, we compute the energy shares in the two subperiods and recalibrate the model to account for the two alternative calibration targets. This changes the values for both η and δ, as detailed in Table 6.

We first simulate the economy without a spillover ($\gamma_1 = \gamma_2 = [0, 0, 0, 0]$), but with different energy shares. Then we simulate the economy with the spillover and different energy shares. In both cases we set the variance of TFP innovations to its average value, after showing that the change in the spillover effect accounts for the majority of the drop in macroeconomic volatility. The first experiment determines whether the change in the energy share alone can account for the Great Moderation. The second experiment determines by how much we enhance our results when, in addition to the spillover, we also allow for a change in the energy share.

Changing only the shares but not the stochastic process between the two periods does not generate a large drop in volatilities of macro variables as documented in Table 7. Output volatility drops by less than 5 percent, consumption volatility by 8 percent, which is much less than what is observed in the data. The investment volatility drops more, though still not close to the drop observed in the data. The reason why the investment volatility drops much more than consumption is because of the complementarity of capital and energy in production. Nakov and Pescatori (forthcoming) find slightly larger estimates of the drop in volatility attributed to a change in the energy share. They report that a 14% drop in output volatility can be accounted for by only changing the energy share parameter. This difference is perhaps due to our assumption of complementarity between capital and energy, in contrast to their Cobb–Douglas assumption. Nevertheless, both numbers—5% and 14%—are relatively small when compared to the drop in volatility caused by the disappearance of the spillover effect from energy prices to TFP.

As expected, the model with the spillover effect and different energy shares explains an even larger decline in the volatility than in the benchmark with fixed energy shares as we demonstrate in Table 8. Output volatility drops by about 40 percent, which accounts for 73 percent of the observed drop in the data, slightly higher than the 68 percent drop in the benchmark calibration. It appears that the reduction in the energy share helps explain some of the Great Moderation but compared to the spillover mechanism its impact is of secondary importance.

Table 8
Volatility in the data versus model: Different energy shares and spillover from the energy price to productivity.

	Early period (1970:I–1982:I)		Late period (1982:II–2006:IV)		Percentage drop in volatility	
	Data	Model	Data	Model	Data	Model
Output	2.52	2.13	1.16	1.28	−54.03	−39.69
Consumption	1.76	0.45	0.73	0.25	−58.55	−43.26
Investment	7.12	10.73	3.63	5.98	−48.91	−44.30
Hours	1.97	1.29	1.12	0.77	−43.27	−39.01

Note: Volatilities refer to the standard deviation of log-deviations from HP-filtered series ($\lambda = 1600$).

5. Conclusion

When simulating Dynamic Stochastic General Equilibrium (DSGE) models, researchers normally assume that the shocks hitting the economy are orthogonal to each other. In our paper we show that innovations to energy prices and total factor productivity (TFP) have not been orthogonal before 1982:II. Subsequently, the two stochastic processes have been close to independent since then. We demonstrate that this change in the structure of the stochastic processes can account for more than 65 percent of the drop in output volatility. Adding the reduced share of energy use to this framework increases the explanatory power of the model to 70 percent.

There are two opposing views in the economics literature on the importance of energy shocks. The empirical literature, for the most part, finds a significant link between energy price shocks and business cycles. On the other hand, the DSGE literature, as in Kim and Loungani (1992) and Dhawan and Jeske (2008), shows that TFP is the main source of business cycle fluctuations, while energy prices play almost no role. Our paper reconciles this disconnect in the following sense. The recessions in the 1970s and 1980s occurred not because of the direct effect of the energy price hikes but because of their spillover effect on productivity on TFP as our model simulation results demonstrate. After 1982:II, this spillover effect disappears which then reduces the volatility of TFP and thus that of macro variables. Hence, one can view our paper as providing a new stylized fact in the Great Moderation debate in the sense that we demonstrate that the drop in TFP volatility has to do with the reduced spillover from energy price shocks.

Currently, we do not take a position on either the source of the spillover in the early period or the reason for its sudden disappearance in the 1980s. Rather, our aim is to establish this new stylized fact and encourage researchers to theoretically account for our empirical findings. For future research it will interesting to determine possible causes for the energy to TFP spillover in the early period as well as reasons for the sudden disappearance after 1982. One possible route is to model the price controls during the Carter and Nixon years that were abolished in the early 1980s. Price controls and the resulting rationing prevent the factor energy from being used in the most productive way. Without explicitly modeling this friction the rationing would show up as lower TFP in response to an energy price shock.

Appendix A. Sampling algorithm

We obtain draws from the posterior distribution using well-known sampling methods. Specifically, we use a Metropolis–Hastings algorithm (see e.g. Robert and Casella, 1999), which consists of the following steps:

1. Denoting by $g(S_t|z_t, z_{t-1}, \theta_z)$ the mass function for S_t (i.e. the filtered probabilities), compute the likelihood function using Hamilton's (1983) filter. This gives $\{g(S_t|z_t, z_{t-1}, \theta_z)\}_{t=5}^{T}$.
2. Couple this likelihood with the prior for θ_z to obtain a draw from the posterior $f_z(\theta_z|\{z_t\}_{t=1}^{T})$.
3. For $t = T-1, T-2, \ldots, 5$, compute the smoothed probabilities given by:

$$g\big(S_t|\{z_t\}, S_{t+1}\big) \propto g(S_{t+1}|S_t)g\big(S_t|\{z_t\}\big) \tag{A.1}$$

4. Repeating the above three steps M times, we obtain M draws from the posterior distribution for θ_z and $\{S_t\}$. We set $M = 30{,}000$ for the estimation of both the energy price and the TFP process and then discarded the first 5000.

Appendix B. Data

We construct the data series as following. The real energy price is the natural logarithm of the quarterly price index of gasoline, fuel energy, natural gas and electricity from the BEA, adjusted by the output deflator net of energy expenditures. Output in the model is given by consumption plus investment. As a result, we construct a price index by weighting the deflator for consumption and investment by the nominal expenditures in each of the two categories. The energy price is a weighted average of the deflator of expenditures in household operation services in electricity and gas (JCSE@USNA),[17] and the deflator of expenditures in gasoline and fuel oil (JCNE@USNA). The weights are given by the relative consumptions in the two categories (CSE@USNA and CNE@USNA).

[17] Throughout we identify variables with their Haver Analytics codes.

In order to obtain good estimates of TFP we use quarterly output data (GDP@USNA) from the BEA and the hours series from the Establishment survey (LPRIVA@USECON). Our measure of output here includes government and the foreign sector, as our measures of capital and employment include all sectors as well. Notice that

$$z_t = y_t\left(\eta k_{t-1}^{\nu} + (1-\eta)e_t^{\nu}\right)^{-\alpha/\nu} h_t^{-1+\alpha} \tag{B.1}$$

As in Cooley and Prescott (1995) we assume that capital is fixed ($k_{t-1} = \bar{k}$) at the quarterly frequency when computing TFP. Firm energy use exists only at the annual frequency, so as a first approximation we assume that e_t is fixed as well. Then, just as in Cooley and Prescott (1995), we construct TFP as

$$\tilde{z}_t = \tilde{y}_t - (1-\alpha)\tilde{h}_t \tag{B.1$'$}$$

where the tilde stand for log-deviations from the trend. Next, we also computed TFP by explicitly taking into account firm energy use by (a) converting the annual energy use into quarterly data by interpolation and (b) by using the quarterly household energy use as a proxy for firm energy use. Since the resulting TFP time series were very similar to the one constructed by assuming fixed energy use (correlation coefficient close to 0.98), and the estimation of the stochastic processes in Section 2 were essentially identical, we kept the same procedure as in Cooley and Prescott for TFP calculation. Finally, as a sensitivity check we also generated artificial data from the model and compared the series for $\tilde{z}_t$ with that of the $\tilde{z}_t$ constructed via equation (B.1′) and again found the two series to be very similar, with a correlation coefficient of 0.95.

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