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Crude Substitution: The Cyclical Dynamics of Oil Prices and the College Premium

Linnea Polgreen and Pedro Silos

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Abstract: Higher oil price shocks benefit unskilled workers relative to skilled workers: Over the business cycle, energy prices and the skill premium display a strong negative correlation. This correlation is robust to different detrending procedures. We construct and estimate a model economy with energy use and heterogeneous skills and study its business cycle implications, in particular the cyclical behavior of oil prices and the skill premium. In our model economy, the skill premium and the ratio of hours worked by skilled workers to hours worked by unskilled workers are both negatively correlated with oil prices over the business cycle. For the skill premium and energy prices to move in opposite directions, the key ingredient is the larger substitutability of capital for unskilled labor than for skilled labor. The negative correlation arises even when energy and capital are fairly good substitutes.

JEL classification: E24, E32, J24

Key words: skill heterogeneity, energy prices, business cycles, capital-skill complementarity

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1 Introduction

Both oil prices and the skill premium (the ratio of the wages of the college-educated to those without a college degree) have been increasing for the past forty years. Despite this increasing trend, when examined closely, oil prices and the skill premium fluctuate in opposite directions, displaying a very strong, negative correlation. This negative correlation is specifically found at the business cycle frequency, and it is robust to different detrending methods.

To examine and quantify the mechansim that leads to the negative correlation between oil prices and the skill premium, we employ a version of the stochastic growth model and conclude that capital-skill complementarity (the idea that capital is more complementary with skilled rather than unskilled labor) drives the inverse relationship between oil prices and the skill premium. Our model includes oil price variations, heterogeneity in skill, capital-skill complementarity and a technology that uses energy as an input. Also, to facilitate parameterization, we combine capital and energy into one term[1].

In our model, oil prices affect both capital usage and energy consumption, and this, in turn, is the driving force behind changes in the skill premium. Specifically, as oil prices increase, energy use decreases which, as long as capital and energy are relative complements[2], reduces the capital-energy composite. A fall in the capital-energy composite increases the demand for unskilled labor relative to skilled labor because unskilled labor is more easily substituted for the capital-energy composite than skilled labor[3]. This

[1]Our capital-energy composite is discussed in section 3.

[2]There is mixed evidence regarding the complementarity of energy and capital (e.g. Pindyck (1979) suggests that in the short run, energy and capital are substitutes, but in the long run they are complements), so we examine cases for which the elasticity of substitution between capital and energy is positive, zero and negative.

[3]See Hamermesh (1993) for a review of the literature.

increasing demand for unskilled labor raises the relative wage of the unskilled and thus decreases the skill premium.

Our model not only accounts for the negative correlation between cyclical movements in oil prices and the skill premium, but also for the relationship between hours worked by skill group and energy prices observed during most of the sample. In our economy, movements in output are almost entirely the result of technology shocks, in agreement with the basic premise of real business cycle models. This is true even though the skill premium is mainly driven by movements in energy prices. Our model also replicates standard business cycle observations, such as the relative volatilities of different aggregated macroeconomic variables (e.g. consumption, investment), as well as their cross-correlations with output.

Energy prices have been largely ignored in the study of the skill premium. To our knowledge this is the first paper that examines the relationship between cyclical movements in the skill premium and oil prices within an equilibrium model of economic fluctuations. Previous studies have focused on either the role of energy in real business cycle economies (e.g. Kim and Loungani (1992)) or the behavior of the skill premium in equilibrium models (e.g. Krussell et al. (2000) and Lindquist (2004))[4]. There is only one paper that specifically examined the effect of oil prices on relative wages: Keane and Prasad (1996) developed an empirical model using panel data and found that skilled, rather than unskilled workers, gain during oil price increases. However, Keane and Prasad used data only covering the period 1966-1981, and we show that their results are driven by the time period considered.

Finally, we contribute to the literature on income inequality over the business cycle (e.g. Castañeda, Díaz-Giménez and Ríos-Rull (2003)). We find that although the ratio

[4]Other related work include Prasad(1996), who analyzed the implications of skill heterogeneity in a business cycle model for the cyclical behavior of in productivity and the real wage, and Castro and Coen-Pirani (2005) who undertake a careful evaluation of the change in the cyclical behavior of aggregate skilled hours after 1984.

of energy expenditures to total capital in the US economy is small, the variability of oil prices is large relative, for instance, to variations in the Solow residuals. We find that the volatility of energy expenditures is a large determinant in the overall variability of the skill premium, previously unaccounted for in other models.

2 Energy Prices and the Labor Market

The skill premium is a weighted ratio of skilled wages to unskilled wages[5]. We define skill by education level: a skilled worker has a college degree, and an unskilled worker does not. Data are obtained from the Current Population Survey (CPS), 1963–2001.

Data on energy prices and usage come from the US Government Energy Information Administration. We use annual data from 1949 to 2001 for prices and quantities of oil, coal and natural gas, which represent almost 85% of overall energy consumption in the US. The price of energy used throughout the analysis is a Laspeyres index of the prices of those three main energy sources. The final energy price index was the result of dividing the constructed energy price index by the Gross Domestic Product deflator.

Using an index of oil, coal and natural gas allows us to compare our results to previous studies, such as Kim and Loungani (1992). Because oil is a large percentage of total energy consumption in the US economy, the deviation from trend of the constructed price index has a very large correlation (about 0.98) with the deviation of oil prices. If oil prices were used instead of the measure used here, all results presented would still hold.

Deviations of the energy price index relative to its HP-trend are shown in Figure 1. Nominal energy prices were very stable until about 1974, decreasing sharply relative to overall inflation. The first oil shock occurs in 1974, when prices rose 78%. The second major oil price increase occurs five years later, during 1979 and 1980, when prices increased

[5] Details are provided in the appendix.

by 27% and 35%, respectively. Large oil price increases did not occur for the next 20 years. However, in 1999, oil prices went up by 21% and by 41% in 2000. After the first two oil crises, there were two large price drops, occurring in 1985 (-52%) and in 1998 (-30%). Thus, overall, energy prices have displayed a large amount of volatility over the last three decades.

Figures 2 - 4 show the detrended skill premium and energy prices, using three types of de-trending methods: deviations from an exponential trend, a (log)HP-filtered series and a (log)band-pass-filtered series. Correlations are negative and in some cases surprisingly strong. For instance, the correlation between the skill premium and energy prices is -0.77 when measured as deviations from an exponential trend. With the other two methods correlations are not as strong but still significant and on the order of -0.4.

As mentioned in Keane and Prasad (1996), the negative correlation between the skill premium and energy prices could be an artifact of aggregation. Wages are only available for the employed, so our skill premium compares the wages of the skilled who are employed to the unskilled who are employed. When energy prices rise, firms that need to cut costs may lay off the lowest-skilled and lowest-paid employees, raising the average wage of the unskilled. The skill premium would rise, even if wages have not changed at all.

However, support for our argument is found by examining the labor input ratio, defined as the hours worked by a skilled worker divided by the hours worked by an unskilled worker. Figure 5 shows the detrended labor input ratio and detrended energy prices. The correlation between these two series is -0.1, which implies that the hours ratio and oil prices are uncorrelated. For most of the series, however, the labor input ratio and oil prices appear to be negatively correlated. The first oil shock is an exception: in 1974 the labor input ratio increased as prices increased, causing the weak correlation. We do not have an explanation for this observation, but firms might have perceived that the oil price shock was temporary. It is usually more difficult to replace high-skilled workers than low-skilled ones, so it might have been optimal to lay off relatively more of the unskilled, increasing the labor input ratio. The importance of the first oil shock in explaining the weak correlation is more clear when we compute a sequence of 9-year rolling correlations with the first ending in 1972 and the last ending in 2001. Both the raw data and a spline-smoothed approximation of these correlations are plotted in Figure 6. After the first oil price shock there is a sharp decline in the correlation between the labor ratio and oil prices, and that correlation stays below zero until the end of the sample. It is clear from the figure that the labor input ratio increased (decreased) when oil prices decreased (increased), approximately after 1978. In fact, using data from 1978 until the end of the sample, the correlation is -0.41. This anomalous behavior during the first oil price shock could partly explain Keane and Prasad's results. Their National Longitudinal Survey of Youth (NLSY) data covered only the period 1966-1981.

Table 1: Volatilities and Correlations with Output
Annual Data (1963-2001)

Variable	Std. Dev. rel. GDP	Correl. with GDP
Consumption	0.59	0.86
Investment	2.96	0.93
Unskilled Hours	0.34	0.73
Skilled Hours	0.27	0.60
Energy Use	1.06	0.31
Energy Prices	8.91	-0.40
Skill Premium	0.82	0.19
Hours Ratio	0.20	-0.36

Finally, Table 1 reports some business cycle statistics for several macroeconomic variables. Consumption (defined as expenditures on non-durables and services), Fixed Investment, Output (the sum of Consumption and Investment) and Energy Use were transformed into per-capita quantities by dividing by the US population, deflated using the GDP deflator, logged and detrended using an HP filter.

Consumption, investment, hours and energy use are all procyclical, although the correlation of energy use with contemporaneous output is rather weak (0.31). The skill premium could be considered almost acyclical: its correlation with GDP is 0.19. This is consistent with other studies of the skill premium over the business cycle, such as Lindquist (2004) who finds, with quarterly data, a correlation closer to zero. Higher energy prices are associated with recessions, and this is reflected in the negative correlation between oil prices and output (-0.30). Finally, the hours ratio (skilled hours over unskilled hours) is also counter-cyclical: its correlation with contemporaneous output is -0.36.

Regarding the relative volatilities, consumption and hours are less volatile than output and investment. The table shows that energy use is roughly as volatile as GDP. However, energy prices are exceptionally volatile – nine times more volatile than GDP.

3 The Model

The economy is populated by a continuum of two types of infinitely-lived agents: skilled and unskilled. Within each type, all agents are identical and individuals may not transit across types. Denote by s the fraction of skilled agents and by u the fraction of unskilled agents, with $s + u = 1$. Agents value consumption and leisure. They rank their options according to the utility function $u(c_{t,j}, 1 - h_{t,j})$, where $c_{t,j}$ and $h_{t,j}$ represent consumption and time spent at work respectively for an agent of type j, $j \in \{u, s\}$. Agents are endowed with one unit of time each period, which they divide between work and leisure, and both types discount the future with a factor β.

There is a representative firm that produces output (Y) using energy (E), capital (K), skilled hours (H_s) and unskilled hours (H_u). Technology is represented by the following constant-returns-to-scale production function:

$$Y_t = z_t G(K_t, E_t, H_{s,t}, H_{u,t}) \tag{1}$$

In the above expression z_t is a random variable representing neutral technological change. The firm uses aggregate hours as their input, so $H_{j,t} = jh_{j,t}$, for $j \in \{s, u\}$. We deviate slightly from previous studies of the skill premium by aggregating all types of capital into one variable K_t [6].

In this economy, markets for goods and factors are competitive. We do not explicitly model the underlying production of energy, and we assume that it involves forgoing a certain amount of consumption and physical capital. The amount needed, however, varies because the relative price of energy (p) with respect to the consumption good evolves exogenously.

The absence of distorting taxes, externalities, etc. allows us to invoke the welfare theorems and solve the associated social planner's problem. The planner maximizes the weighted sum of utilities for the two types of agents by choosing sequences of capital, consumption, labor and energy. Formally the problem can be stated as:

$$\max_{\{c_{t,s}, c_{t,u}, h_{t,s}, h_{t,u}, E_t, K_{t+1}\}} E \sum_{t=0}^{\infty} \beta^t \{\Psi s \left[u(c_{t,s}, 1 - h_{t,s})\right]\} + (1 - \Psi) u \left[u(c_{t,u}, 1 - h_{t,u})\right]\} \quad (2)$$

s.t.

$$sc_{t,s} + uc_{t,u} + p_t E_t + K_{t+1} \leq Y_t + (1 - \gamma) K_t$$

$$H_{t,j} = jh_{t,j}$$

$$Y_t = z_t G(K_t, E_t, H_{t,u}, H_{t,u})$$

$$H_{t,s}, H_{t,u}, C_{t,s}, C_{t,u} > 0$$

Denoting by η the vector of exogenous shocks $(\log z_t, \log p_t)'$, we assume that it follows a first-order Markov process:

$$\eta_t = \Phi \eta_{t-1} + \nu_t \quad \nu_t \sim N(0, \Omega). \quad (3)$$

[6] We are aware of the advantages of separating total capital into structures and equipment; the faster decline of equipment prices helps to understand the evolution of the skill premium at lower frequencies. We have chosen this simpler approach because we believe that for the goal of this paper, it suffices to have only one type of capital. Also, it clarifies the exposition.

Innovations to technology and oil prices can be contemporaneously correlated, i.e. Ω is unrestricted. The companion matrix Φ is restricted to be diagonal for simplicity. An equilibrium for this model is a set of decision rules for the endogenous variables, given exogenous shocks and parameters, which solve the planner's problem, and a set of factor prices that are equal to the marginal products of skilled labor, unskilled labor and capital.

4 Parameterization

We restrict preferences to be of the logarithmic class with separability between consumption and leisure,

$$u(c_{t,j}, 1-h_{t,j}) = \theta log(c_{t,j}) + (1-\theta) log(1-h_{t,j}), \quad i \in \{j, s\}$$

with the parameter θ representing the "expenditure" share of each of the two goods. Note that preferences are identical for each of the two types of agents.

Output is obtained using capital, energy and labor and produced according to the following nested-CES production function,

$$Y_t = z_t \{\xi(\alpha \tilde{K}_t^{\phi} + (1-\alpha) H_{t,s}^{\phi})^{\frac{\delta}{\phi}} + (1-\xi) H_{t,u}^{\delta}\}^{\frac{1}{\delta}}.$$

The variable $\tilde{K}_t$ is the capital-energy composite:

$$\tilde{K}_t = \{\mu K_t^{\nu} + (1-\mu) E_t^{\nu}\}^{\frac{1}{\nu}}.$$

We write production in this way because we will (rather loosely) interpret our capital-energy composite as the measure of capital used in other studies in order to assign values to some parameters.

Obtaining quantitative conclusions requires parameterizing the model in a realistic way. In principle, it is possible to estimate the model by maximum likelihood using well-known methods. However, in early attempts, the likelihood function was ill-behaved, so we used a simulated quasi-maximum likelihood method, augmenting the estimation with prior distributions over the structural parameters of the model. The estimation procedure[7], in short, maximizes a likelihood function (the quasi-likelihood function) that differs from the exact likelihood of the model economy. Let θ be a vector of structural parameters (describing preferences, technology, etc.) and let $\{\tilde{y}\}_{t=1}^{S} = f(\theta, \{\eta_t\}_{t=1}^{S})$ be the output from the model. $\{\tilde{y}\}_{t=1}^{S}$ is a vector of time series of GDP, employment, energy use, etc. of length S, which is an unknown function of the structural parameters and the sequence of realizations of the two shocks. The estimation procedure fits a reduced-form statistical model to $\{\tilde{y}\}_{t=1}^{S}$, in our case a VAR, with a well-defined likelihood function yielding a set of parameters $\beta(\theta)$ (in our case, the OLS estimates of the VAR). Denote this likelihood function by $L(\{\tilde{y}\}_{t=1}^{S}; \beta(\theta))$. The quasi-likelihood function of the model is $L(\{Y\}_{t=1}^{T}; \beta(\theta))$, where $\{Y\}_{t=1}^{T}$ is the empirical counterpart of $\tilde{y}$ obtained from actual US data.

We augmented this quasi-likelihood function with prior distributions over the structural parameters, $p(\theta)$. We believe that incorporating prior information about the parameters is an advantage, not a drawback, of this Bayesian approach and we summarize this information in the form of probability density functions. Coupling the quasi-likelihood function with the prior distributions we obtained our "quasi-posterior" distribution $P(\theta|\{Y\}_{t=1}^{T}) \propto L(\{Y\}_{t=1}^{T}|\theta)p(\theta)$. We simulated a long sequence of draws from the quasi-posterior distribution using well-known sampling procedures (see, for example, Fernández-Villaverde and Rubio-Ramírez (2004))[8].

The entire vector to be estimated was $(\beta, \psi, \theta, \xi, \alpha, \mu, \nu, \delta, \gamma, \phi, \rho_p, \rho_z, \sigma_{pz}, \sigma_p, \sigma_z)'$. To facilitate the estimation we fixed some parameters that have clear empirical counterparts

[7] Interested readers are referred to Smith's (1993) work for a more detailed explanation.

[8] For a given vector of parameter values, the model's solution is found by log-linearizing the optimality conditions and the constraints, and solving for the expectation functions using the methods described in Klein (2000). A Technical Appendix at the end describes the precise equations used when solving the model.

and whose values have been estimated elsewhere in the literature. For instance, the depreciation rate of capital γ was set at 0.1, and the discount factor β was set at 0.96 (values widely used with annual data). The three parameters that drive the elasticities of substitution between the different factors are ϕ, δ and ν. We loosely assigned ϕ, the parameter driving the elasticity of substitution between skilled labor and the capital-energy composite, a value consistent with estimates found in previous studies. Krusell et al. (2000) estimate ϕ to be -0.45, while Polgreen and Silos (2006), building on Krusell et al.'s analysis, find values for ϕ between -0.16 and -0.60. We used the Krusell et al. estimate. Similarly δ, the elasticity of substitution between unskilled labor and capital, was assigned a value of 0.5. Estimates for the substitutability of energy and capital vary widely: work using time-series data find values that imply that both inputs are more complementary than a Cobb-Douglas energy-capital aggregator would imply, while conclusions from cross-sectional studies point towards more substitutability than Cobb-Douglas. We have set the parameter ν to -0.7, the estimated value in Morrison and Berndt (1981), also used in Kim and Loungani (1992). However, the importance of the value of ν will be the object of a detailed discussion below. Finally the fraction of skilled workers s was set to 0.28, the average for our sample period. The persistence parameter ρ_p and the variance of the noise σ_p^2 in the oil price shock equation (3) were fixed at 0.846 and 0.062 respectively.

The remaining parameters $(\psi, \theta, \xi, \alpha, \mu, \rho_z, \sigma_{pz}, \sigma_z)'$ were estimated. We used three different observables: real output, consumption and energy use[9]. The data were logged and HP-filtered prior to estimation.

The prior distributions for the parameters were all independent and either normal or gamma. We did perform some prior predictive analysis to guide us in the choice and shape of $p(\theta)$. As a result, we centered the distribution for μ, the weight of capital in the capital-energy composite, at 0.97 with a standard deviation of 0.05, in order to attain a

[9] A section below provides some sensitivity analyses with respect to changes in the choice of observables.

small energy-to-capital ratio, as observed in US data. We had less prior information about the remaining weights in the production function – α and ξ had normal prior distributions centered at 0.5 with a standard deviation of 0.1 – the same distribution as the planner's weight Ψ. The parameter that represents preferences for consumption θ was given a prior mean of 0.7 with a standard deviation of 0.05. Regarding eq. 3, the prior mean of ρ_z was 0.9 and the standard deviation 0.03; the covariance between the two shocks (σ_{pz}) was endowed with a normal distribution with a mean of -0.001 and a standard deviation of 2×10^{-4}. Finally, the prior distribution for the variance of the productivity shock was gamma with parameters 10 and 1×10^{-4}, which implies a mean of 1×10^{-3} and a standard deviation of 3×10^{-4}. All the normal distributions were truncated to the appropriate regions.

The posterior means and standard deviations of the estimated parameters are given in Table 2. Although the prior distributions were quite informative, for several parameters the posterior distributions were centered at considerable distance from the prior means. For example, the weight of capital μ has a posterior mean of 0.90, which is more than two standard deviations away from the prior mean. The distributions of the other production function parameters, ξ and α, were each displaced by approximately one standard deviation. The other parameters' distributions shifted less profoundly.

Table 2: Posterior Means and Standard Deviations

Parameter	Mean (Std. Dev.)
Ψ	0.472 (0.074)
ξ	0.655 (0.102)
α	0.611 (0.046)
μ	0.903 (0.013)
θ	0.749 (0.049)
ρ_z	0.910 (0.013)
σ_{pz}	-1.2$\times 10^{-3}$ (2×10^{-4})
σ_z^2	1.2$\times 10^{-4}$ (2.0×10^{-5})

5 Results

The model was quantitatively evaluated in the standard way. After solving for the policy functions and simulating the shock processes using the parameters presented above, we obtained a set of time series of interest. We treat these series in the same way as the true data – first logged, then HP-filtered. We present moments (standard deviations and contemporaneous correlations with output[10]) of the deviations of variables from their HP trend. Table 3 presents measures of volatility for a few macroeconomic aggregates, with standard errors in parentheses[11]:

Table 3: Standard Deviations (in %)

Variable	Std. Dev. (Std. Error)
Y	5.35 (0.52)
C	1.83 (0.24)
I	18.92 (2.21)
H_s	0.87 (0.27)
H_u	0.53 (0.23)
E	18.26 (0.32)
w_s/w_u	2.75 (0.37)
H_s/H_u	0.29 (0.21)

The model's implications regarding standard deviations are broadly consistent with US data: consumption and hours are less volatile than income, which is less volatile than investment. Quantitatively, energy use is too volatile in the model: its standard deviation relative to that of GDP is more than three. In the data the standard deviations of energy and GDP are about the same. Finally, both the skill premium and the hours ratio are

[10] We have decided not to overwhelm the reader with columns of data on cross-correlations with GDP at different leads and lags. These are, of course, available upon request for any of the parameterizations in the paper.

[11] The standard errors are posterior standard deviations of the standard deviations themselves. For each of the draws of θ, the vector of structural parameters, we solved for the decision rules and simulated the economy, therefore obtaining an entire distribution of the standard deviations and correlations with output of any aggregate variable. The standard errors are not a result of simulating time series of different lengths and then averaging over them, as is sometimes done in the macroeconomic literature.

significantly less volatile than output, as is observed empirically.

The contemporaneous correlations with output are shown in Table 4.

Table 4: Correlations with Output

Variable	Correlation (Std. Error)
C	0.708 (0.044)
I	0.819 (0.043)
H_s	0.826 (0.054)
H_u	0.428 (0.113)
E	0.783 (0.044)
w_s/w_u	0.755 (0.082)
H_s/H_u	0.587 (0.160)

Consumption, investment and production inputs are all procyclical as in the data, although the correlation between energy use and output is much stronger in the model. The same can be said for the skill premium, which is mildly procyclical in the data but has a correlation higher than 0.7 in the model. Finally, it is the correlation between output and the hours ratio in which the model fares worst: it is countercyclical in the data but procyclical in the model. A subsection below will analyze whether increasing the substitutability between capital and energy can improve along these dimensions.

The correlations between the skill premium and energy prices, as well as the relationship between oil prices and the relative labor ratio, are presented in Figure 7. There is a great deal of uncertainty in the model about the value of the correlation between the hours ratio and oil prices: the posterior density for this correlation covers a wide range – from -1 to 0 – with a substantial amount of mass between -0.1 and 0. The posterior distribution for the correlation between the skill premium and oil prices is much tighter, and according to the model, values larger than -0.8 are unlikely.

Finally, our model also has implications for the volatility of the skill premium itself. Table 1 reports that the skill premium's volatility relative to GDP in annual US data is

0.82. As is clear from Table 3, the model delivers a volatility substantially lower than what is observed in the data: the ratio of the volatility of the skill premium to that of GDP is only 0.17.

The model contains both TFP and oil-price shocks, but we want to determine how much of the variance of the skill premium is attributable to oil-price shocks only. Results for this experiment are presented in Table 6. We show the standard deviation of the skill premium relative to that of output and the standard deviation of the skill premium itself. These are computed for three distinct economies: one where the only shocks are oil price shocks, one where the only shocks are TFP shocks and one where both shocks hit the economy.

Table 5: Relative Contributions of Shocks to Skill Premium Variation

Shock	$std(SP)/STD(GDP)$	$std(SP)$ (in %)
p	0.83	0.85
z	0.07	0.33
Both	0.17	0.86

Energy price shocks are an important source of fluctuations in the skill premium. Quantitatively they are considerably more important than TFP shocks. In fact, in economies where the only shocks are energy shocks, the volatility of the skill premium relative to that of GDP matches the data: we observe a ratio of approximately 0.80. Even in the case of high substitutability between capital and energy, this ratio is only 0.22 when both shocks are present. Because of the neutrality of the TFP shock, one would expect that energy prices would be relatively more important in explaining movements in the skill premium. Nevertheless, quantitatively the difference is large: energy shocks matter.

5.1 Alternative Parameterizations

Next we analyze the effects of changing the previous parameterization. First, we will explore the implications of reducing the complementarity between capital and energy. Second, we use time series of different macroeconomic variables in the estimation procedure.

Previously we assumed a value of ν equal to -0.7, which implies that energy and capital are relative complements. Now we relax this assumption, and allow energy and capital to become more substitutable. We assess the resultant changes in the correlations of oil prices with both the skill premium and the hours ratio. Figure 8 shows the posterior distributions of the correlation between the skill premium and oil prices for three different values of ν: -0.7, 0, and 0.3 [12]. These three values correspond, respectively, to more, about the same and less complementarity than a Cobb-Douglas capital-energy aggregator. The remaining parameters in the model were fixed at the values shown in Table 2.

Considering the correlation between the skill premium and energy prices (figure 8), the posterior distribution for the higher complementarity cases is tighter than for the lowest complementarity case. Also the average values of the correlations are non-monotonic: the "close-to-Cobb-Douglas" case implies a smaller correlation than the higher complementarity case, which in turn implies a smaller correlation than the higher substitutability case. In understanding the relationship between the skill premium and energy prices, it is key to understand the behavior of the capital-energy composite in the face of an oil price shock. More substitution implies that when the economy is hit by a price shock, capital and energy will move in opposite directions; complementarity implies that they will move together. By keeping all other parameters fixed, the larger the substitutability between capital and energy, the smaller the volatility of the capital-energy composite, and

[12] The value of ν was not exactly zero. We set it at 0.001.

therefore the smaller the volatility of the skill premium.

Figure 9 shows the posterior distributions for the correlation between the hours ratio ($\frac{H_s}{H_u}$) and oil prices. The uncertainty is large, and all cases have at least some mass at values close to zero. The figure shows that as we increase substitutability between energy and capital, the correlation between the hours ratio and energy prices increases. (This is the expected result). Thus, assuming capital-energy complementarity is not necessary to generate a negative correlation between oil prices and the skill premium.

Next we examine the sensitivity of the model's results to changing the time series used in the estimation. Recall that the series used in the previous section were real per capita consumption, output and energy expenditures. The two panels in Table 6 show the standard deviations and the contemporaneous correlations with output for the same aggregates as those shown in Tables 3 and 4. Each column uses different combinations of time series in the estimation procedure described above. The series are real per capita consumption (C), investment (I), output (Y), energy expenditures (E) and employment (N). We produced results using output, consumption and employment (YCN); output, investment and energy expenditures (YIE); and output, investment and employment (YIN).

Table 6a: Standard Deviations (alt. estimation)

YCN: Output, Consumption, Employment

YIE: Output, Investment, Energy

YIN: Output, Investment, Employment

Variable	YCN	YIE	YIN
Y	7.26 (0.88)	4.97 (0.67)	3.78 (0.27)
C	2.06 (0.16)	1.28 (0.12)	1.72 (0.13)
I	16.9 (1.10)	26.7 (2.04)	9.91 (0.79)
H_s	0.88 (0.14)	2.09 (0.40)	0.18 (0.04)
H_u	0.99 (0.17)	0.21 (0.06)	1.22 (0.14)
E	18.3 (0.25)	17.8 (0.27)	16.0 (0.19)
w_s/w_u	2.23 (0.25)	1.46 (0.35)	1.89 (0.18)
H_s/H_u	1.05 (0.11)	2.00 (0.38)	1.17 (0.14)

Table 6b: Correlation with Output (alt. estimation)

Variable	YCN	YIE	YIN
C	0.74 (0.02)	0.76 (0.05)	0.81 (0.02)
I	0.70 (0.04)	0.66 (0.03)	0.90 (0.03)
H_s	0.68 (0.05)	0.61 (0.06)	0.90 (0.02)
H_u	0.40 (0.07)	0.56 (0.03)	0.23 (0.11))
E	0.59 (0.06)	0.54 (0.07))	0.84 (0.06))
w_s/w_u	0.60 (0.07)	0.30 (0.12)	0.90 (0.04)
H_s/H_u	0.19 (0.14)	0.58 (0.06)	-0.11 (0.13)

Most of the qualitative results shown in Tables 3 and 4 still hold. In particular, consumption, energy use, investment and employment are procyclical. Investment and energy use are substantially more volatile than the other aggregates, although there are some large quantitative differences. For instance, the ratio of investment to output volatility is 5.4 for the YIE parameterization, substantially larger than for the other cases. The standard deviation of skilled hours relative to unskilled hours seems to be quite sensitive to the series used: the YIE value is 10 times larger than the YIN value. Skilled hours are even more volatile than consumption in the YIE case. The YIN parameterization implies a negative correlation between the relative hours ratio and output – this is the correct sign, which we were unable to obtain with our original parameterization. However, the standard deviation of this estimate is large, and zero is within one standard deviation of its mean.

Finally, Figures 10 and 11 show the posterior distributions of the correlations of the skill premium with oil prices and the correlation of the relative hours ratio with oil prices, respectively. All the parameterizations show negative correlations between the skill premium and oil prices, and distributions differ only in their tightness. The sign of the correlation coefficient between oil prices and the relative hours ratio is more sensitive to alternative parameterizations: the YIN case displays a distribution for that correlation that has very small mass for negative values. The other two cases show the opposite, with one of the distributions (YCN) having a very small variance centered around -0.9.

6 Conclusion

The relative wage that a skilled worker earns relative to that earned by an unskilled worker, the skill premium, is negatively correlated with oil prices at the business cycle frequency. This observation is robust to different de-trending methods, and this correlation is surprisingly strong.

Previous researchers using different data sets and sample periods have found the opposite: a negative oil price shock benefits skilled workers relative to unskilled workers. However, these results depended upon the time period considered. We show that the negative correlation between energy prices and the skill premium follows from a real business cycle model using reasonable assumptions: when the model is forced to match a few moments from the data, the negative correlation obtains, even for a high degree of substitutability between energy and capital. A key ingredient in the model is the larger substitutability of capital for unskilled labor than for skilled labor. However, this is not controversial: a wide body of research has found some degree of capital-skill complementarity in the US economy (e.g. Griliches (1969), Krusell et al. (2000)). Also, capital-skill complementarity has been used to explain the low frequency movements of the skill premium (e.g. Krusell et al. (2000)).

Finally, we show the importance of energy-price shocks on explaining the variation of the skill premium. Energy-price shocks are quantitatively much more important than TFP shocks, and in economies where the only source of uncertainty is oil price shocks, we are able to account for the volatility of the skill premium relative to that of GDP.

A Data

The skill premium is calculated using a method from Polgreen and Silos (2006). We obtain data from the CPS (March out-going rotation) and include anyone who is at least 16 but not over 70 years old. We include only those who have wage and salary income. (This excludes the self employed.) Many observations have missing hours: the CPS asks what one's income was last year, but how many hours one worked last week. Thus, interviewees who were on vacation or on any other type of leave during the previous week would have income from last year, but no hours for last week. In order to retain as many observations as possible, we impute missing hours. Hours are estimated using age, age^2, years of education and dummy variables representing female, black, and white. We then eliminate any observation that is missing any necessary variable or has unreasonable hourly wages[13].

The hours variable is then multiplied by the number of weeks worked last year to obtain annual hours. The annual hours, l, are weighted by the CPS weights, μ, and an ability index, $w_{g,96}$, representing the average wage in 1996 of similar individuals, g. Annual hours, l, are summed over all observations in each skill level, j, to obtain the labor input series[14], N.

$$N_{j,t} = \sum_{i \epsilon G_{j,t}} l_{i,t} w_{g,96} \mu_{i,t},$$

where i represents each observation, and t represents the year. The wage is calculated by multiplying the wage, $w_{i,t}$, by the annual hours variable and the CPS weights, summing

[13] Following Card and DiNardo 2002), we consider unreasonable wages to be less than \$1 or greater than \$100 in 1979 dollars.

[14] The sample is divided into 264 groups based on age, race, gender and education level, and we calculate the average wage of each group in 1996 to create an ability index. To make the index unitless and to avoid problems with inflation, the index is then divided by the average wage in 1996 for each skill level. This is an appropriate ability index: if one's wage represents one's marginal product, those with higher wages represent a larger amount of labor input per hour. See Denison (1979).

over all observations for each skill level, and dividing by the labor input series.

$$W_{j,t} = \frac{\sum_{g \epsilon G_{j,t}} w_{i,t} l_{i,t} \mu_{i,t}}{N_{j,t}}.$$

The numerator is the total wage bill: the average wage in the group times the average labor input in the group, weighted by the CPS weights. This is divided by the labor input, N, to get the wage series for both the skilled and the unskilled. The skill premium is then calculated by dividing the wage series for the skilled by the wage series for the unskilled.

B Model Solution

The planner solves the following problem:

$$\max_{\{c_{t,s}, c_{t,u}, h_{t,s}, h_{t,u}, E_t, K_{t+1}\}} E \sum_{t=0}^{\infty} \beta^t \{\Psi s\left[u(c_{t,s}, 1 - h_{t,s})\right]\} + (1 - \Psi) u\left[u(c_{t,u}, 1 - h_{t,u})\right]\}$$

s.t.

$$sc_{t,s} + uc_{t,u} + p_t E_t + K_{t+1} \leq Y_t + (1 - \gamma) K_t$$

$$H_{t,j} = j h_{t,j}$$

$$Y_t = z_t G(K_t, E_t, H_{t,u}, H_{t,u})$$

$$H_{t,s}, H_{t,u}, C_{t,s}, C_{t,u} > 0$$

The marginal products of the four production inputs are:

$$\frac{\delta G}{\delta h_{u,t}} = (1 - \xi)(\xi(\alpha(\mu k_t^{\nu} + (1 - \mu) e_t^{\nu})^{\frac{\phi}{\nu}} + (1 - \alpha) h_{s,t}^{\phi})^{\frac{\delta}{\phi}} + (1 - \xi) h_{u,t}^{\delta})^{\frac{1}{\delta} - 1} h_{u,t}^{\delta - 1}$$

$$\frac{\delta G}{\delta h_{s,t}} = (1 - \alpha)\xi(\xi(\alpha(\mu k_t^{\nu} + (1 - \mu) e_t^{\nu})^{\frac{\phi}{\nu}} + (1 - \alpha) h_{s,t}^{\phi})^{\frac{\delta}{\phi}} + (1 - \xi) h_{u,t}^{\delta})^{\frac{1}{\delta} - 1}(\alpha(\mu k_t^{\nu}$$

$$+ (1 - \mu) e_t^{\nu})^{\frac{\phi}{\nu}} + (1 - \alpha) h_{s,t}^{\phi})^{\frac{\delta}{\phi} - 1} h_{s,t}^{\phi - 1}$$

$$\frac{\delta G}{\delta k_t} = \xi\alpha\mu(\xi(\alpha(\mu k_t^{\nu} + (1 - \mu) e_t^{\nu})^{\frac{\phi}{\nu}} + (1 - \alpha) h_{s,t}^{\phi})^{\frac{\delta}{\phi}} + (1 - \xi) h_{u,t}^{\delta})^{\frac{1}{\delta} - 1}(\alpha(\mu k_t^{\nu} + (1 - \mu) e_t^{\nu})^{\frac{\phi}{\nu}}$$

$$+(1-\alpha)h_{s,t}^{\phi})^{\frac{\delta}{\phi}-1}(\mu k_t^{\nu}+(1-\mu)e_t^{\nu})^{\frac{\phi}{\nu}-1}k_t^{v-1}$$

$$\frac{\delta G}{\delta e_t}=\xi\alpha(1-\mu)(\xi(\alpha(\mu k_t^{\nu}+(1-\mu)e_t^{\nu})^{\frac{\phi}{\nu}}+(1-\alpha)h_{s,t}^{\phi})^{\frac{\delta}{\phi}}+(1-\xi)h_{u,t}^{\delta})^{\frac{1}{\delta}-1}(\alpha(\mu k_t^{\nu}+(1-\mu)e_t^{\nu})^{\frac{\phi}{\nu}}$$

$$+(1-\alpha)h_{s,t}^{\phi})^{\frac{\delta}{\phi}-1}(\mu k_t^{\nu}+(1-\mu)e_t^{\nu})^{\frac{\phi}{\nu}-1}e_t^{v-1}$$

The first-order necessary conditions are given by:

$$(1)\ \ \frac{\Psi\theta s}{c_{t,s}}=\lambda_t$$

$$(2)\ \ \frac{(1-\Psi)\theta u}{c_{t,u}}=\lambda_t$$

$$(3)\ \ \frac{\Psi(1-\theta)s}{1-h_{t,s}}=\lambda_t z_t\frac{\delta G}{\delta h_{s,t}}$$

$$(4)\ \ \frac{(1-\Psi)(1-\theta)u}{1-h_{t,s}}=\lambda_t z_t\frac{\delta G}{\delta h_{u,t}}$$

$$(5)\ \ \lambda_t=\beta E_t\lambda_{t+1}\{z_{t+1}\frac{\delta G}{\delta k_{t+1}}+(1-\gamma)\}$$

$$(6)\ \ p_t=z_t\frac{\delta G}{e_t}$$

The log-linearized versions of equations (1)-(6) coupled with the laws of motion for the two shocks and the (log-linearized) aggregate resource constraint yield solutions for the percentage deviations from the steady state for the nine variables $(\lambda, c_u, c_s, h_u, h_s, y, e, k, z, p)'$.

References

[1] Card, D. and DiNardo, J. (2002), "Skill-Biased Technological Change and Rising Wage Inequality: Some Problems and Puzzles", *Journal of Labor Economics*, vol 20, no. 4, pp. 733–81.

[2] Castañeda, A., Díaz-Giménez, J. and Ríos-Rull, J.V. (2003), "Accounting for Earnings and Wealth Inequality", *Journal of Political Economy*, vol. 111, no. 4, pp. 818-857.

[3] Castro, R. and Coen-Pirani, D. (2005), "Why Have Aggregate Skilled Hours Become So Cyclical since the Mid-1980s?", manuscript, Université de Montreal.

[4] Denison, E. (1979), *Accounting for Slower Economic Growth: The United States in the 1970s*, The Brookings Institution, Washington D.C.

[5] Fernández-Villaverde, J. and Rubio-Ramírez, J. (2005), "Estimating Dynamic Equilibrium Economies: Linear vs. Nonlinear Likelihood", *Journal of Applied Econometrics*, 20, 891-910.

[6] Griliches Z. (1969), "Capital-Skill Complementarity", *Review of Economics and Statistics*, Vol. 51(4), pp. 465-468.

[7] Hamermesh D. (1993), *Labor Demand*, Princeton University Press, Princeton, NJ.

[8] Keane M. and Prasad E. (1996), "The Employment and Wage Effects of Oil Price Changes: A Sectoral Analysis", *The Review of Economics and Statistics*, Vol. 78, pp. 389-400.

[9] Kim I. and Loungani P. (1992), "The Role of Energy in Real Business Cycle Models", *Journal of Monetary Economics*, Vol. 29, pp. 173-189.

[10] Klein P. (2000), "Using the Generalized Schur Form to Solve a Multivariate Linear Rational Expectations Model", *Journal of Economic Dynamics and Control*, Vol. 24(10), pp. 1405-1423.

[11] Krusell P., Ohanian L., Ríos-Rull J.V., and Violante G. (2000), "Capital-Skill Complementarity and Inequality: A Macroeconomic Analysis", *Econometrica*, Vol. 68(5), pp. 1029-1054.

[12] Lindquist M. (2004), "Capital-Skill Complementarity and Inequality Over the Business Cycle", *Review of Economic Dynamics*, Vol. 7, pp. 519-540.

[13] Morrison C.J. and Berndt E. (1981), "Short-Run Labor Productivity in a Dynamic Model", *Journal of Econometrics*, Vol. 16, pp. 339-365.

[14] Pindyck R. (1979), *The Structure of World Energy Demand*, The M.I.T. Press, Cambridge, MA.

[15] Polgreen L. and Silos P. (2006), "Capital Skill Complementarity and Inequality: A Sensitivity Analysis", Federal Reserve Bank of Atlanta WP-2005-20.

[16] Prasad E. (1996), "Skill Heterogeneity and the Business Cycle", *Canadian Journal of Economics*, Vol. 29(4), pp. 910-929.

[17] Smith, A. A., (1993), "Estimating Non-Linear Time Series Models Using Simulated Vector-Autoregressions", *Journal of Applied Econometrics*, 8, S63-S84.

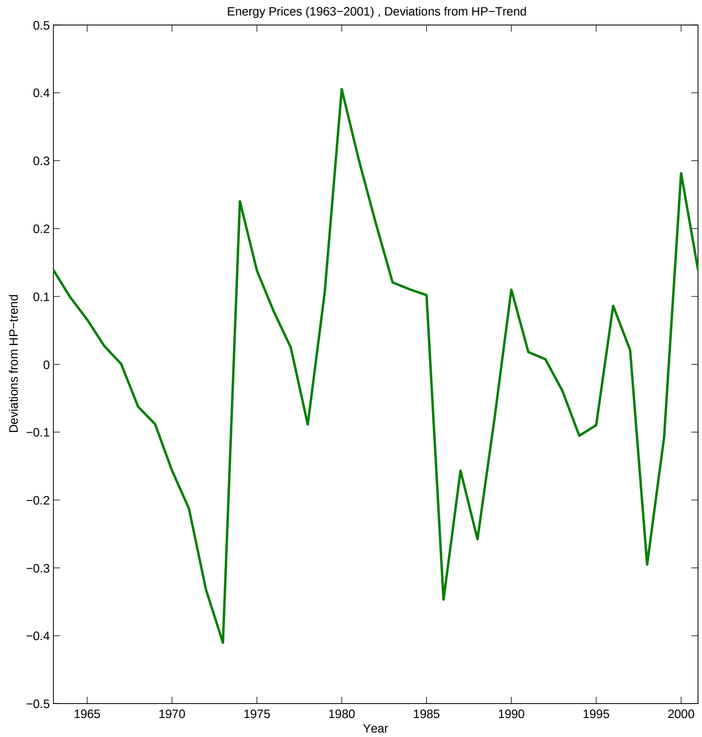

Figure 1: Deviations from an HP-trend of energy prices. US data, annual, 1963-2001.

Figure 2: Deviations from an exponential trend of energy prices and the skill premium. US data, annual, 1963-2001.

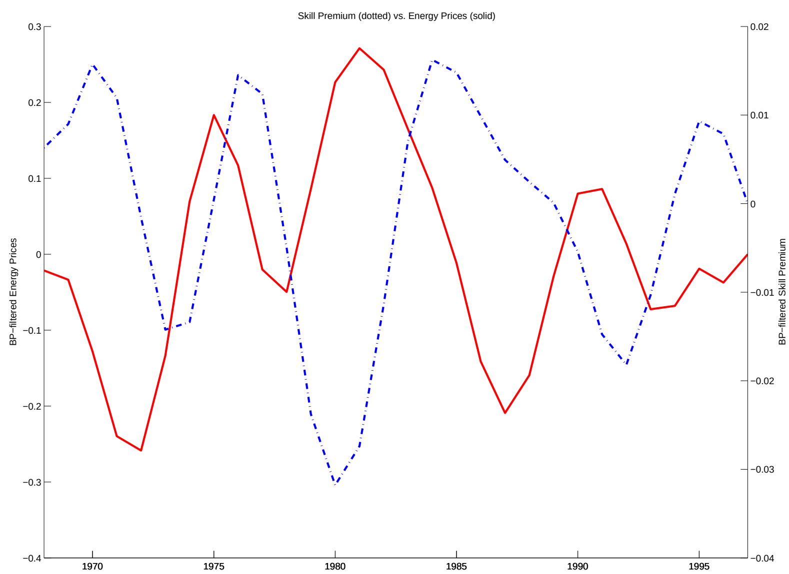

Figure 3: Band-pass filtered energy prices and skill premium. US data, annual, 1963-2001.

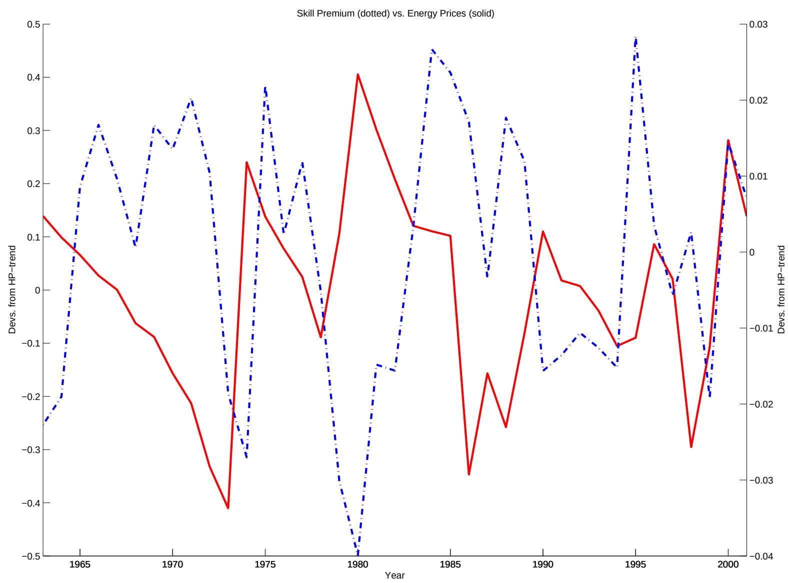

Figure 4: Deviations from an HP-trend of energy prices and the skill premium. US data, annual, 1963-2001.

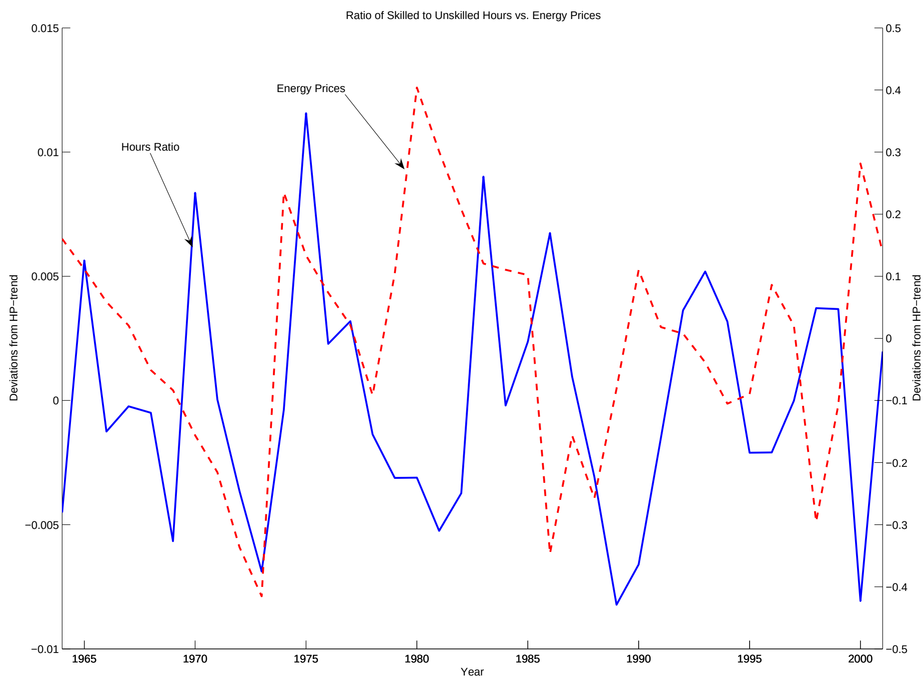

Figure 5: Deviations from an HP-trend of energy prices and the relative hours ratio. US data, annual, 1964-2001.

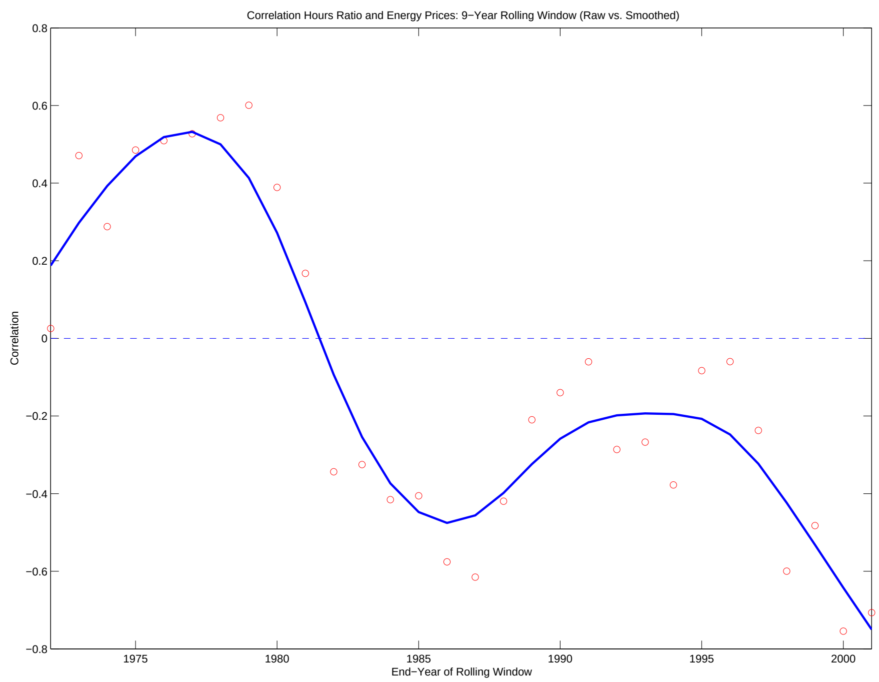

Figure 6: Sequence of 9-year rolling correlations between energy prices and the relative hours ratio. The solid line is the spline-smoothed approximation of the scatter-plot

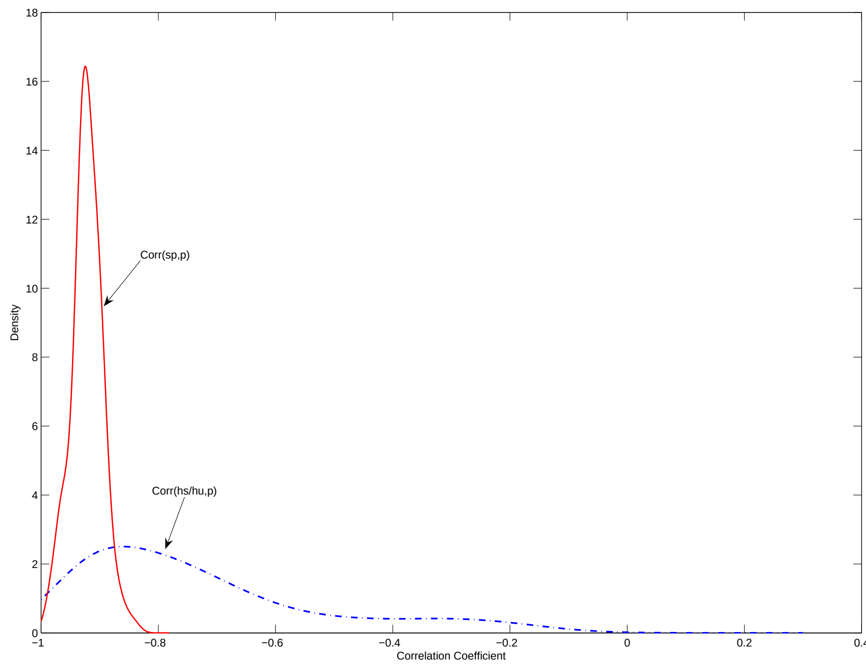

Figure 7: Correlations of the skill premium with oil prices (red solid line) and the hours ratio with oil prices (blue dash-dotted line).

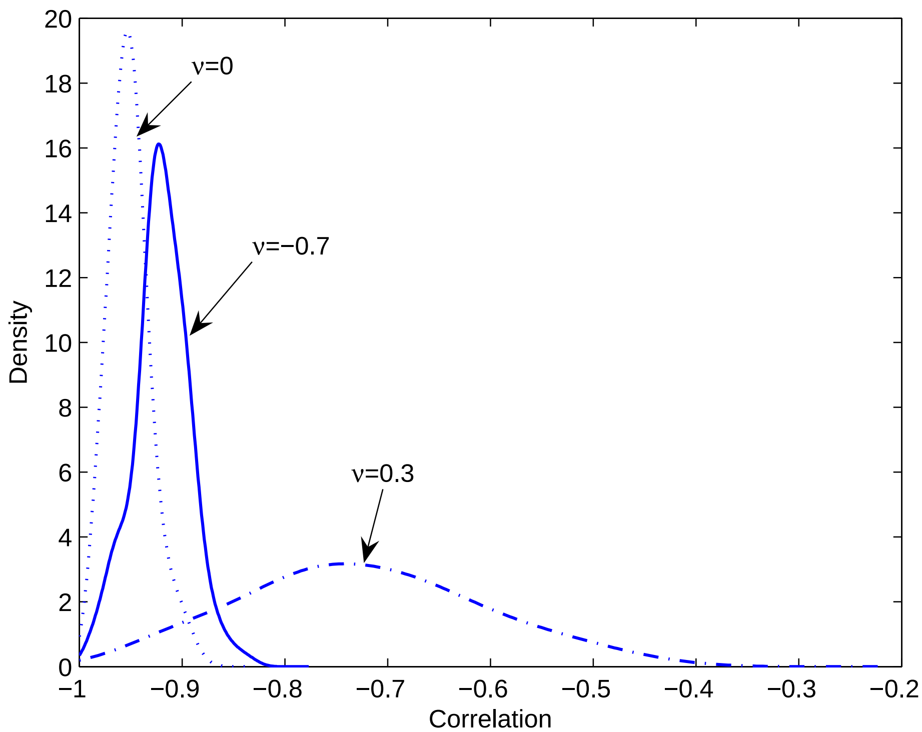

Figure 8: Posterior distribution of the correlation between oil prices and the skill premium in the model for three different values of ν.

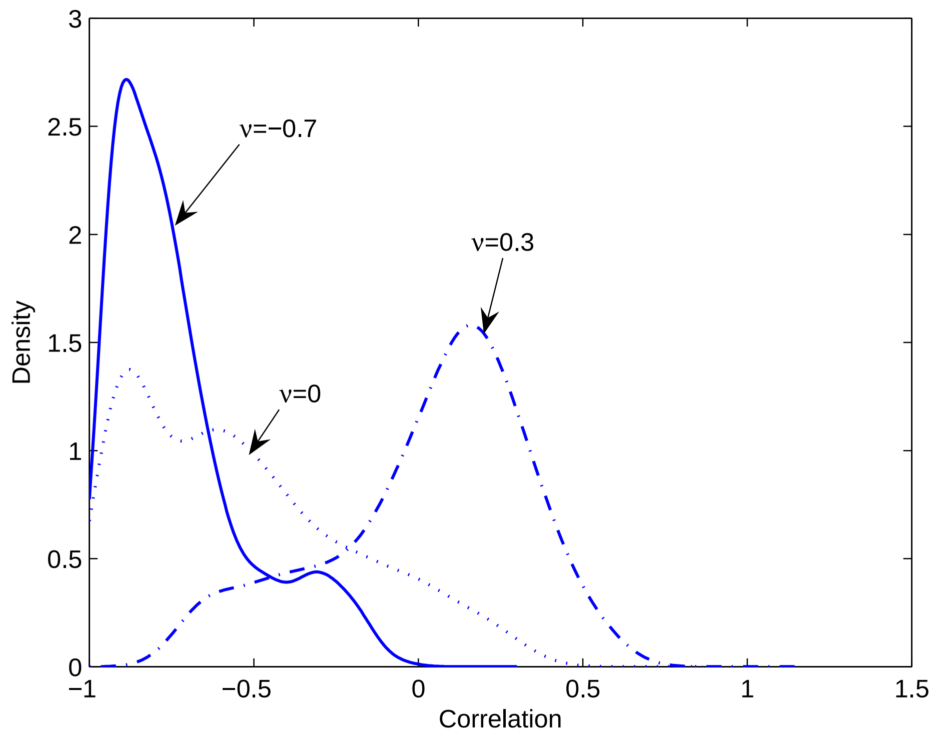

Figure 9: Posterior distribution of the correlation between oil prices and the relative hours ratio in the model for three different values of ν.

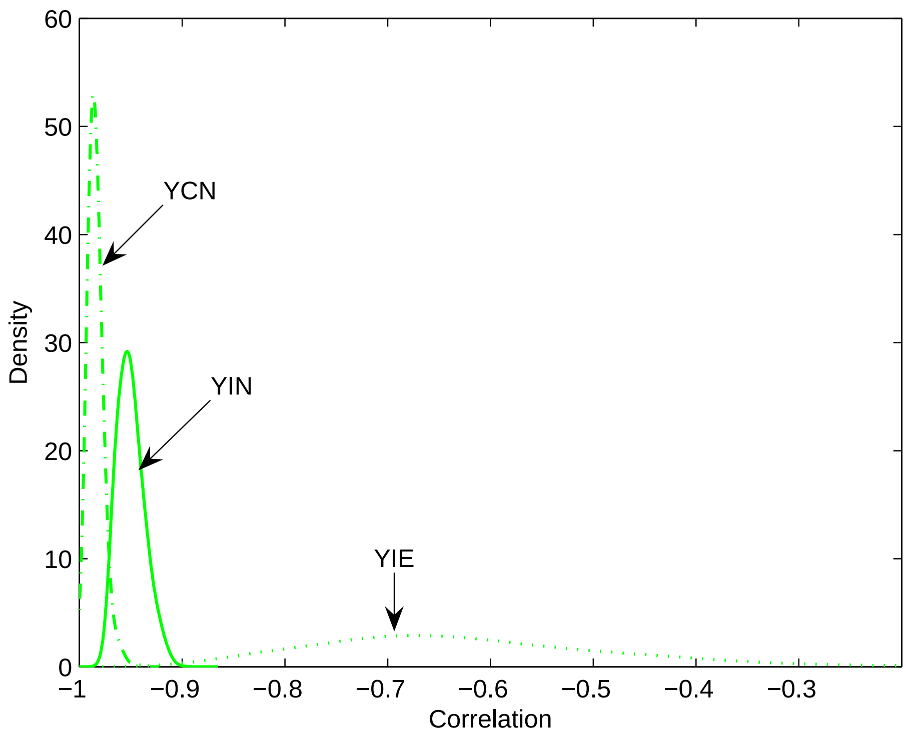

Figure 10: Posterior distribution of the correlation between oil prices and the skill premium in the model for three different sets of estimated parameters.

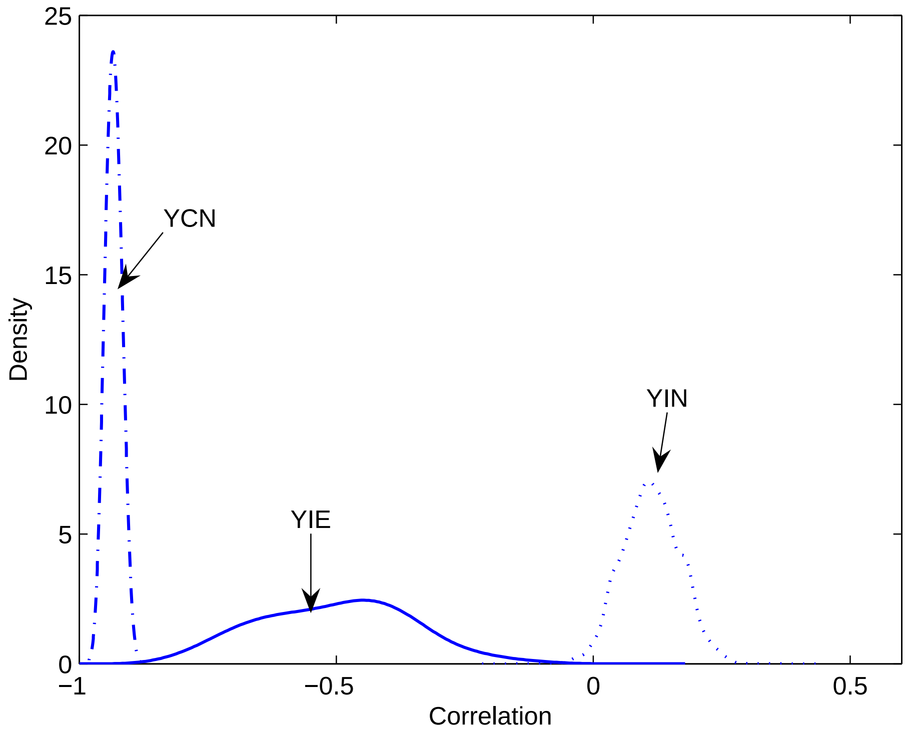

Figure 11: Posterior distribution of the correlation between oil prices and the relative hours ratio in the model for three different sets of estimated parameters.