Does Oil Price Uncertainty Affect Energy Use?

Gerard H. Kuper\textsuperscript{a} and Daan P. van Soest\textsuperscript{b}

\textsuperscript{a}Department of Economics and SOM, University of Groningen, The Netherlands
\textsuperscript{b}Department of Economics and CentER, Tilburg University, The Netherlands

Abstract

Theory predicts that the presence of fixed costs implies that the relationship between energy use and energy price changes is asymmetric, as the firm’s output and investment decisions respond differently to energy price increases and decreases. The asymmetry is exacerbated if future energy prices are uncertain, but to date the empirical literature does not explicitly take uncertainty into account. The contribution of this paper is twofold. First, we develop a new measure of energy price uncertainty. Second, we apply this measure to explain energy use in fifteen OECD countries between 1978 and 1996. Our results support the theoretical prediction that energy price uncertainty affects the asymmetry and renders energy-saving technologies less attractive.

Keywords: Volatility, uncertainty, GARCH, oil prices.

JEL Classification: C22, Q43.
1. Introduction

The recent literature on the consequences of energy prices changes for investment and GDP growth predicts that investment behavior reacts asymmetrically to energy price increases and price decreases. This asymmetry is caused by irreversibility of investment decisions. If a change in energy prices induces firms to adopt new technologies, one does not expect them to instantaneously undo the investment if the energy price change is reversed (e.g. Dixit and Pindyck 1994). For example, insulation put in when energy prices increase is not pulled out when prices subsequently drop.

In addition, theory predicts that uncertainty about future energy prices renders investment behavior even more sluggish. The argument is that energy price uncertainty implies that there is a non–zero probability that energy price change reversals take place. If such a reversal takes place, firm managers may regret having invested in a new technology, especially if that technology was purchased to better gear the firm’s production process to the (relative) prices in the economy. Also, it is argued that the higher the level of energy price uncertainty, the larger the magnitudes of the price change reversals – if they occur. Hence, to reduce the probability of ex–post regretting the adoption of a new – for example, energy–saving – technology, firms postpone investment in new capital goods. In fact, when facing uncertainty, firms should use an investment criterion that is more stringent than standard expected net present value analysis. Waiting for new information to arrive over time reduces the probability of the investment turning out to be ex–post unprofitable (see Bernanke 1983, Pindyck 1991, Dixit and Pindyck 1994).

These insights are obtained from the so-called real options theory, which predicts that the fixed adjustment costs (investments) have a profound effect on the relationship between energy price changes and energy price use. Higher energy price uncertainty implies that firms will respond more slowly to energy
price increases (or decreases) as they postpone the required investments. And if they do adjust their production processes, energy prices will have to fall (or increase) even more before the investment is reversed. However, the production technology actually in use is an important determinant of actual energy use, but it is obviously not the only one. Indeed, the way in which the technology is actually run, is also important. That means that substitutability of inputs as well as, for example, ‘good housekeeping’ are also expected to affect energy use, and may render the relationship between energy use, energy prices and energy price uncertainty less straightforward than predicted by the real options theory described above.

By now there is a considerable empirical literature that supports the theoretical prediction with respect to the fundamental asymmetry between changes in energy prices and the change in the amount of energy consumed both at the micro and macro level. Examples include Gately (1992), Dargay and Gately (1994), Ferderer (1996), Hooker (1997, 2002), Balke et al. (2002), Hamilton (2003), and Hamilton and Herrera (2004). With the notable exception of Ferderer (1996), none of these papers explicitly analyzes the role of uncertainty in the asymmetry.

This paper explores the importance of energy price uncertainty on the amount of energy used, while allowing for the relationship between energy price changes and adjustment in energy demand to be asymmetric. However, we do not use Ferderer’s (1996) unconditional standard deviation in the oil price as a measure of energy price uncertainty.\(^1\) As we will show in section 4, oil price volatility is clustered, and this serial correlation in the variance of oil prices implies that if price volatility is high in one period, it is expected to be high in

\(^1\) So, rather than using multi–fuel (energy) prices Ferderer (1996) uses oil prices as a proxy for energy prices; energy markets are sufficiently well-integrated that oil price volatility is a good proxy of general energy price uncertainty. As high–frequency energy price data are not available for a
later periods as well. The fact that there is serial correlation in volatility is expected to have more profound consequences for the economy than if volatility were a ‘random draw’. The latter would imply that if volatility is high today, it may very well be close to zero tomorrow, whereas the former indicates that if volatility is high today, it is likely to be high tomorrow as well. Theory predicts that this serial correlation in uncertainty is expected to deter investment even more if uncertainty is of the former rather than of the latter kind (see also Dixit and Pindyck 1994).

We conjecture that managers running energy–intensive firms are aware of the fact that volatility is clustered, and hence that they realize that higher current levels of uncertainty also imply larger uncertainty with respect to the immediate future. That means that we need to construct a measure of uncertainty (or volatility) that captures this phenomenon. AutoRegressive Conditional Heteroscedasticity (ARCH) models have been developed to capture volatility clustering, and therefore we propose to use the conditional (time–variant) standard deviations of oil prices – as obtained by ARCH regressions – as a measure of energy price uncertainty. The conditional standard deviations obtained by means of ARCH models are the one–period ahead forecast standard deviations based on past information, and hence are more likely to be a correct representation of firm managers’ expectations about future uncertainty –based on past experience– than unconditional standard deviations.

Our paper contributes to the literature in two respects. First, it provides a new measure of energy price uncertainty, which captures volatility clustering. Second, it uses that measure to analyze the fundamental relationship between sufficiently long time span whereas oil price data are, we also use oil price data to construct a proxy for energy price uncertainty.
energy use and energy prices, using annual data on fifteen OECD countries over the period 1978–1996.\textsuperscript{2}

The policy relevance of this analysis is evident. Energy economics is a field with a strong modelling tradition, often aimed at analysing the economic consequences of a wide diversity of policy issues ranging from strategic energy–dependency considerations to environmental concerns. Price elasticities of energy demand are key parameters in these models, and hence a better understanding of the relationship between energy use, energy prices changes and energy price uncertainty allows for more effective policies with respect to energy use (e.g., Bhattacharyya 1996; Bunn and Larsen 1997). For example, the insights provided by this paper help identify economic circumstances in which policies aimed at reducing energy use (e.g., the Kyoto Protocol) are likely to be more effective. Is energy demand more responsive to changes in energy prices (and hence to energy taxes) in periods of economic booms (relatively low energy prices that increase over time) or in recession periods (relatively high energy prices that may or may not fall over time)? (Incorrect) estimates of the price elasticity of energy demand also affect the choice of instruments. Taxes are generally preferred in terms of dynamic efficiency (Requate and Unold 2003) and are hence the optimal instrument in times of economic calm, but tradable permits may be the preferred instrument in uncertain times because of the cap they impose on the total amount of energy used. But the analysis provided here also broadens the scope of policy instruments to include those aimed at reducing uncertainty. This includes the option of mitigating price uncertainty by means of price regulation, trading off the potential costs of such a policy (in terms of

\textsuperscript{2} Note that to fully capture the impact of volatility clustering on investment decisions, a structural model of energy demand needs to be constructed in which clustering of energy price volatility is accounted for. The agent’s maximization problem then depends explicitly on the estimated parameters of a (G)ARCH model. In this respect, this paper only provides the first step in showing the relevance of properly measuring uncertainty, thus underlining the necessity of taking a more structural approach.
inefficiencies) against its benefits of having more effective instruments; cf. Dosi and Moretto (1997).

The setup of this paper is as follows. The next section argues that a proper measure of uncertainty must take account of volatility clustering because of its impact on expectations (as argued above). ARCH models are designed to do just that, and section 3 briefly introduces the various classes of ARCH models that are potential candidates to base our measure on, and in section 4 we select the appropriate specification. Our focus is on energy price uncertainty, but we construct our measure of volatility using data on oil price fluctuations. Energy markets are sufficiently well-integrated that oil price volatility is a good proxy of energy price uncertainty (cf. Ferderer 1996), and oil price data are available on a monthly (and even daily) basis. Volatility clustering is present in these oil price data, and we use Generalized ARCH (GARCH) models to capture this clustering. To apply the uncertainty measure in our energy model using annual data, we need to transform the monthly conditional variance obtained via a GARCH model into a measure that reflects within–year energy price uncertainty (as in Bollerslev et al. 1994, p. 3012), and this is done in section 5.

The uncertainty measure thus derived is applied in section 6 for models that relate energy prices to economic activity. Whereas the regression model itself is very straightforward, actually estimating it is not. The reason for this is the high degree of multicollinearity between the explanatory variables, which forces us to choose between two submodel specifications, one where uncertainty affects the energy price elasticity asymmetrically (i.e., its impact differs in periods of price increases and decreases), and one where its impact is symmetric. The estimation results are presented in section 7, which shows that the relationship between energy price changes and changes in economic activity is asymmetric, and that price elasticity of energy demand is smaller the more uncertain future energy prices. Section 8 summarizes our main findings.
2. Measuring uncertainty

Before addressing the importance of energy price uncertainty on energy use, it is necessary to first discuss how energy price uncertainty should be measured. Federer (1996) calculates energy price uncertainty as the within-month standard deviation of daily oil prices. Many economic time series applications, however, suggest that the variance of the error term varies over time in relation to the volatility of errors in the immediate past. This clustering of large and small errors may be observed for exchange rates, stock market returns, interest rates, and option prices. Although we postpone our formal tests to a later section, just looking at monthly refiner acquisition cost of imported crude oil in figure 1 (as measured in terms of US$ per barrel; see also Appendix A) suggests that oil price changes are no exception.

When confronted with the decision to adopt new technologies in response to changes in energy prices, entrepreneurs should take into account (i) that high levels of volatility imply that there is a probability that energy price change reversals take place³, and also (ii) that the magnitude of the price change reversal is larger the higher the level of volatility. When they occur, energy price change reversals may render energy–related investments ex–post unprofitable. Volatility clustering means that volatility shocks today give rise to high levels of volatility many periods in the future, and hence high volatility today implies that the

³ Obviously, higher levels of volatility are not only observed to result in larger (unfavorable) price change reversals, but also in larger price changes that are favorable. However, as implied by the literature on option pricing (Dixit and Pindyck 1994, Pindyck 1991), the possibility of receiving ‘bad news’ in the (near) future has a larger impact on investment behavior than the possibility of receiving ‘good news’ (even if the probabilities of each occurring are equal) as the negative consequences of bad news can be mitigated by postponing the investment decision. In other words, keeping one’s options open reduces the probability of regret.
probability of unprofitable energy price change reversals is likely to remain high for a fairly long period in the foreseeable future.

We hypothesize that managers of (energy–intensive) firms are aware of both the consequences of the presence of uncertainty itself (i.e., that they consider postponing the investment decision if energy prices are very volatile) as well as of the fact that volatility is correlated over time. Serial correlation of volatility means that using straightforward standard deviations of energy price changes does not suffice; we need a measure of volatility that takes into account the serial correlation observed in past periods. Therefore, we propose a measure based on the *conditional* standard deviation as derived from univariate GARCH models. The conditional standard deviations thus obtained are the one–period ahead forecast standard deviations based on past information, and hence capture the firm managers’ previous period’s experience on the basis of which they are likely to make their forecasts about the future.

3. **Accounting for volatility clustering**

We use fluctuations in oil prices as an indicator of general energy price uncertainty. Information on oil prices is available on a monthly or even daily basis. Daily data have the advantage of a larger number of observations, which allows a more thorough testing of the importance of shorter–term lags in determining variances. Unfortunately, the most often used daily time series is that on Brent oil prices, and it goes back only to January 1982. As our OECD data set starts in 1978, we will use monthly data (that are available for the entire sample period) to construct our volatility measure and apply this measure in models that aim to explain energy use.4

Table 1 shows that the average percentage change in monthly oil prices (between 1970–2002 as measured by US refiners’ acquisition costs) is about zero
with a standard deviation of 0.80. But these log–differenced oil prices show an asymmetric distribution, with a long right tail (positive skewedness), and peaked relative to the normal distribution (kurtosis coefficient>3). Autocorrelations of log–differenced oil prices and of squared log–differenced oil prices suggest dependence in the mean, but also reveal dependence in volatility (see table 2).\footnote{INSERT TABLES 1 AND 2 ABOUT HERE}

Neglecting the exact nature of the dependence of the variance of the error term conditional on past volatility results in loss of statistical efficiency, which ARCH models were precisely developed to correct (see Engle 1982, Bollerslev et al. 1994). By using the conditional standard deviation as derived from ARCH models, we capture the fact that volatility is clustered over time, and this may be a better measure of uncertainty as perceived by firm managers than the simple standard deviation of energy prices as traditionally used.

Let us first determine whether indeed volatility is serially correlated over time. Various versions of Generalized ARCH models are potential candidates (Bollerslev 1986). Defining $\varepsilon_t^2$ as the variance of the error term $\varepsilon_t$ in a generalized regression equation where the dependent variable $y_t$ (in our case, the log–differenced oil price), is determined by a set of regressors $x_t$ (e.g., a constant as well as lagged log–differenced oil prices),

$$y_t = x'_t \beta + \varepsilon_t,$$

\footnote{Monthly observations yield conditional variances that are similar to conditional variances based on daily data (see Kuper 2002 for more details).}

\footnote{We have made sure that the big ‘political and economic events’ alone are not responsible for the dependence in the mean and in volatility observed. When omitting the years 1986 and 1991 (see figure 1) associated with these events, we still find that autocorrelations of the log–differenced oil prices and of squared log–differenced oil prices indicate that ARCH models should be used.}
one can test whether the conditional variance $\sigma_t^2$ is affected by conditional variances $q$ periods in the past ($\sigma_{t-i}^2, \ i=1,\ldots, \ q$) as well as by $p$ lags of the unconditional variance terms ($\epsilon_{t-i}^2, \ i=1,\ldots, \ p$). This is done by determining the significance of parameters $\alpha_i$ and $\lambda_j$ in the following relationship:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \epsilon_{t-i}^2 + \sum_{j=1}^{p} \lambda_j \sigma_{t-j}^2,$$

where $\alpha_0 > 0, \alpha_i \geq 0, \lambda_j \geq 0$. This model is referred to as a GARCH($p,q$).

The simplest version of this model, GARCH(1,1), provides a good description of the data in many applications. Well-defined conditional variances require that the parameters $\alpha_0, \alpha_1$, and $\lambda_1$ are non-negative. The estimate $\hat{\alpha}_1 + \hat{\lambda}_1$ is a measure of persistence: the average time for volatility to return to the mean is $1/(1-(\hat{\alpha}_1 + \hat{\lambda}_1))$. If the estimate for $\hat{\alpha}_1 + \hat{\lambda}_1$ in the GARCH(1,1) model is close to unity, the model is not covariance stationary (the process is an integrated GARCH process). In that case the model can be used only to describe short-term volatility.

Note that in the symmetric model (equation 2) the conditional variance is a function of the size and not of the sign of lagged residuals. One way to allow for asymmetries is the Threshold GARCH (TARCH) model (see Glosten et al. 1993, Zakoian 1994):

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \epsilon_{t-i}^2 + \sum_{j=1}^{p} \lambda_j \sigma_{t-j}^2 + \psi \epsilon_{t-1}^2,$$
where $\delta_i = 1$ if $e_i < 0$, and 0 otherwise. The coefficient $\gamma$ measures the leverage effect. In this model, good news ($e_i < 0$) and bad news ($e_i > 0$) have different effects on the conditional variance. Good news has an impact of $\alpha_i$, while bad news has an impact of $\alpha_i + \gamma$.

An alternative model that allows for asymmetric shocks to volatility is the Exponential GARCH (EGARCH) model (see Nelson 1991):

$$\ln(\sigma_t^2) = \alpha_0 + \sum_{i=1}^{q} \alpha_i \frac{|e_{t-i}|}{\sigma_{t-i}} + \sum_{j=1}^{p} \beta_j \ln(\sigma_{t-j}^2) + \sum_{i=1}^{p} \gamma_i \left( \frac{e_{t-i}}{\sigma_{t-i}} \right).$$

(4)

The coefficients $\gamma_i$ measure the leverage effects. In the next section, we test whether leverage effects are present in time series for oil prices.

4. Estimation results

We apply the GARCH($p,q$) model to the log–differenced monthly oil price (see figure 1 above) rather than to the actual price level as the latter is not found to be stationary. We use a simple univariate specification in which the mean equation (1) includes a constant and an AR(1)–term as is suggested by the autocorrelations in table 2 above. The sample period is January 1970 until April 2002.

Estimating the mean equation (1) using (2) for a wide range of values for $p$ and $q$, the Schwarz Information Criterion suggests that $p=1$ and $q=1$. The results are presented in table 3.

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6 Unit–root tests (including a constant, no trend and 4 lags) do not reject the hypothesis of a unit root at 5%. The ADF test statistic equals −2.204 which, in absolute value, is smaller than the 5% critical value (−2.869). However, these tests have only little power if errors are not homogeneous (Kim and Schmidt 1993), or in the presence of structural breaks (Perron 1989). Therefore, the results of these tests should be interpreted with caution.
The usual assumption that standard errors $\varepsilon_t$ are Gaussian, is violated and hence we report the quasi–maximum likelihood covariances and standard errors described by Bollerslev and Wooldridge (1992). The ARCH LM test indicates that there is no autoregressive conditional heteroskedasticity up to order 10 in the standardized residuals. An alternative test is the Ljung–Box Q–statistic of the standardized squared residuals. At the tenth lag Q equals 16.557 indicating that the standardized squared residuals are serially uncorrelated. From these tests we conclude that the volatility model is adequate.\(^7\) Table 3 shows that $\hat{\lambda}_1 + \hat{\lambda}_4 = 0.89$, which means that the effect of a change in volatility is persistent. The average time for volatility to return to the mean is $1/(1 - (\hat{\lambda}_1 + \hat{\lambda}_4)) = 9$ months. However, the Wald test does not reject the null of an integrated GARCH process, so we cannot reject the hypothesis that the volatility process does not return to its mean. This is an important result given the prevalence of the “reversion to mean” mentality – in terms of both price levels and price volatility – among oil market analysts.

These results demonstrate that the variance of the (log–differenced) oil price series is indeed affected by previous realizations, which indicates that high levels of volatility today imply that future price uncertainty remains high as well. However, this model assumes that positive and negative shocks affect the conditional variance similarly; the conditional variance is assumed to be a function of just the size and not of the sign of the lagged residuals. To detect whether asymmetries exist in the relationship between lagged residuals and the observed variance as calculated by (1), we use both the TARCH and EGARCH models discussed in section 3.

\(^7\) This is confirmed by GARCH models based on over 5,000 daily observations (see Kuper 2002 for more details).
Table 4 summarizes the results for the asymmetric specifications. The results for both the TARCH(1,1) and the EGARCH(1,1) model indicate that the leverage effect term $\gamma$ is not significantly positive. Thus, the volatility process itself is not asymmetric, and hence equations (1) and (2) provide the appropriate model. The conditional standard deviation of the GARCH(1,1) model is plotted in figure 2.

Although the volatility process itself is found to be symmetric, the effect of volatility on economic performance may well be asymmetric. To show the impact of volatility of oil prices on economic activity, we need to construct models of economic activity. The data for these models are annual data, which implies that the monthly volatility measure derived here needs to be aggregated to reflect annual volatility.

5. Measure of uncertainty

The GARCH models using monthly data in the previous sections generate conditional standard deviations for the corresponding time spans. To obtain a measure of uncertainty experienced during a specific year, we consider two alternatives: the average conditional standard deviation over the twelve months in year $t$ $(\frac{1}{12} \sum_{t = 1}^{12} \sigma_{\tau, t})$, and the highest monthly conditional standard deviation in that year $(\max_{t \in \{Jan, \ldots, Dec\}} \sigma_{\tau, t})$. As the regression results using either uncertainty measure are identical qualitatively (although not quantitatively), we
focus on average conditional standard deviation, but the results using the alternative are available upon request.

The average conditional standard deviation, denoted by \( Z_t \) 
\[
(\frac{1}{T} \sum_{t=1}^{T} \sigma_t ) 
\]
(\( \sigma_t \) is plotted in figure 3.

INSERT FIGURE 3 ABOUT HERE

What we observe in figure 3 is that uncertainty has been extremely high in the years 1973–1974 (the oil embargo). After the oil embargo in 1973–1974 uncertainty dropped to low levels until the mid 1980s. Since 1995 uncertainty seems to increase. Volatility peaks are observed in 1974, 1986, 1990, 1994, and 1999 and at the start of the 21st century. The causes, both political and economic, are reflected in the events detailed in Appendix A.

The relationship between these events and oil price volatility is interesting in itself, but more interesting is the question of how uncertainty affects the economy. Basically, we expect firms to postpone investments when energy price uncertainty (as reflected by the variability of oil prices) is high; rational firms keep their options open. The tendency to postpone is likely to be even stronger because uncertainty is found to be correlated over time, which implies that uncertainty today influences expectations about the future. A related question is whether these responses are the same in magnitude in periods of energy price increases and decreases. These questions will be addressed in the next section.

6. **Asymmetric effects of uncertainty on the use of energy**

In addition to developing this new measure of uncertainty, this paper aims to test its robustness by applying it in models of energy use, thus providing additional insight into the role of uncertainty in energy use. We have compiled a consistent dataset consisting of fifteen countries (indexed \( j \)) with nine industries
(indexed $i$) each for the period 1978–1996 (indexed $t$). The list of variables includes industry–specific energy prices (calculated using domestic prices of energy carriers weighted by the amount of each source of energy used by the industry under consideration), the amount of energy used, the amount of output produced, and also labor input and industry–specific wage rates. For a more detailed description of the OECD data set, see Appendix B.

The uncertainty measure from the previous section ($Z_t$) is included in two simple models. The first model relates energy use ($E_{ijt}$) to the price of energy (deflated using industry-specific producer price indices; $P_{ijt}^E$) and output ($Y_{ijt}$; also measured in real terms). It is a short–run energy demand equation assuming exogenous energy prices and output:

$$d \log(E_{ijt}) = \alpha_U + \beta_U d \log(P_{ijt}^E) + \delta_U d \log(Y_{ijt}) + \epsilon_{U,ijt}, \quad (5)$$

where subscript $U$ denotes that the coefficients are specific to the regression that aims to determine the percentage change in energy use.$^8$

The second model focuses on energy intensity of production and relates the energy–labor ratio ($E_{ijt}/L_{ijt}$) to the exogenous relative price of energy to labor ($P_{ijt}^E/W_{ijt}$):

$$d \log(E_{ijt} / L_{ijt}) = \alpha_I + \beta_I d \log(P_{ijt}^E / W_{ijt}) + \epsilon_{I,ijt}, \quad (6)$$

$^8$ This simple specification is warranted because endogeneity of prices and quantities does not constitute a problem here. Our data are at the sectoral level, and we can safely assume that none of the sectors in none of the countries included in our data set has any market power on the energy market. That means that the price of energy (as well as its volatility) is exogenous. In addition, shifts in the demand function itself are instrumented for by including sectoral output.
where subscript $I$ indicates that the coefficients are specific to the regression that aims to determine the percentage change in energy intensity (i.e., relative input use). The rationale behind this model is that entrepreneurs, in the long run, adjust the energy intensity of production to the price of energy relative to the wage rate.

We extend these models to include both energy price uncertainty, and possible asymmetries with respect to energy price changes.$^9$ Asymmetry works directly through prices, and uncertainty generally renders energy demand less elastic. To allow for uncertainty and asymmetry, we adjust Models (5) and (6) as follows:

\[
\begin{align*}
    d \log(E_{ijt}) &= \alpha_U + \beta_U d \log(P_{ijt}^E) + \mu_U \left[ d \log(P_{ijt}^E) \right] + \lambda_U Z_t \times d \log(P_{ijt}^E) + \\
    &+ \gamma_U Z_t \times \left[ d \log(P_{ijt}^E) \right] + \delta_U d \log(Y_{ijt}) + \epsilon_{U,ijt}. \\

    d \log(E_{ijt} / L_{ijt}) &= \alpha_I + \beta_I d \log(P_{ijt}^E / W_{ijt}) + \mu_I \left[ d \log(P_{ijt}^E / W_{ijt}) \right] \\
    &+ \lambda_I Z_t \times d \log(P_{ijt}^E / W_{ijt}) + \gamma_I Z_t \times \left[ d \log(P_{ijt}^E / W_{ijt}) \right] + \epsilon_{I,ijt}.
\end{align*}
\]

Recall that $Z_t$ is the average conditional standard deviation over the twelve months in year $t$ ($Z_t = \frac{1}{12} \sum_{r=1}^{12} \sigma_{1,12} \sigma_{t} \sigma_{r,t}$). As stated in the introduction, we assume that the current conditional volatility level is the best available predictor of future uncertainty. We have interacted this uncertainty measure with all explanatory variables (the percentage change in (relative) energy prices as well as the absolute levels of these percentage changes). If the coefficients on the regression terms that include $Z_t$ turn out to be insignificant (that is, if $\gamma_k = \lambda_k = 0$, for $k=U$ in equation 7 and $k=I$ in equation 8, respectively), volatility is not found to affect the price elasticity of energy demand.

\[\text{Appendix B shows that the standard deviation of energy price changes dominates the standard deviation of nominal wage rates. This is why we do not include uncertainty surrounding nominal wage rates.}\]
The absolute values of the percentage changes in (relative) energy prices are included as explanatory variables in (7) and (8) to capture asymmetry in the response of energy use to price increases and decreases. If the coefficients on the absolute values of these variables fail to be significant (i.e., $\mu_k = \gamma_k = 0$ for $k=U$ in equation (7) and $k=I$ in equation (8)), we can conclude that energy demand responds symmetrically to both increases and decreases in energy prices (as captured by $\beta_k$, $k=U, I$ in equations (7) and (8) respectively) as well as with respect to the impact of price uncertainty ($\lambda_U$, respectively $\lambda_I$ in equations (7) and (8)). If the parameters of the absolute variables ($\mu_k$ and $\gamma_k$) are significantly different from zero, then energy demand responds asymmetrically to changes in energy prices. Price uncertainty affects the responsiveness of energy demand to changes in energy prices ($\lambda_k$) and the extent of the asymmetry ($\gamma_k$).

Equations (7) and (8) provide full flexibility with respect to decomposing the impact of energy price changes into asymmetric components, where the actual extent of the impact is allowed to differ depending on the amount of uncertainty the industry is confronted with. Unfortunately, pretesting indicates that multicollinearity between the variables with and without the uncertainty measure is such that equations (7) and (8) cannot be estimated directly. That means that we have to choose between two, more restricted, specifications; one in which the coefficients $\beta_k$ and $\gamma_k$ are set equal to zero, and one in which $\mu_k$ and $\lambda_k$ are set equal to zero. We refer to these submodels as specifications I and II, respectively:

\[
\begin{align*}
    d \log(E_{ijt}) &= \alpha_U + \mu_U \left[d \log(P_{ijt}^E)\right] + \lambda_U Z_t \times d \log(P_{ijt}^E) + \delta_U d \log(Y_{ijt}) + \epsilon_{U,ijt} \\
    (7-I)
\end{align*}
\]

\[
\begin{align*}
    d \log(E_{ijt}) &= \alpha_I + \beta_U d \log(P_{ijt}^E) + \gamma_I Z_t \times \left[d \log(P_{ijt}^E)\right] + \delta_I d \log(Y_{ijt}) + \epsilon_{U,ijt} 
\end{align*}
\]
and

$$d \log \left( \frac{E_{ijt}}{L_{ijt}} \right) = \alpha_I + \mu_I d \log \left( \frac{P_{ijt}^E}{W_{ijt}} \right) + \lambda_I Z_t \times d \log \left( \frac{P_{ijt}^E}{W_{ijt}} \right) + \epsilon_{t,ijt}$$

(8–I)

$$d \log \left( \frac{E_{ijt}}{L_{ijt}} \right) = \alpha_I + \beta_I d \log \left( \frac{P_{ijt}^E}{W_{ijt}} \right) + \gamma_I Z_t \times d \log \left( \frac{P_{ijt}^E}{W_{ijt}} \right) + \epsilon_{t,ijt}.$$  

(8–II)

In these submodels energy price increases and energy price decreases have different effects on energy use. Both specifications (I) and (II) thus allow for asymmetric responses in energy use to changes in the energy price. However, they differ with respect to how they treat uncertainty. In specification (I), energy use responds asymmetrically to energy price changes (if $\mu_k \neq 0, k = U, I$), but energy price uncertainty does not increase or decrease this asymmetry. However, it does affect the price elasticity (if $\lambda_k \neq 0, k = U, I$). In specification (II), however, $Z_t$ interacts with the absolute value of the price change, which implies that uncertainty affects the asymmetric response of energy use to energy price changes (if $\gamma_k \neq 0, k = U, I$).

To illustrate the effect of uncertainty on the price elasticity of energy use we assume that (confirmed by econometric estimates below) $\beta_k < 0$, $\gamma_k < 0$, $\mu_k > 0$, and $\lambda_k > 0$, for $k = U, I$. Economic intuition is that the price elasticity of energy use is negative (i.e. energy use falls (rises) if the price of energy increases (decreases)), and we choose parameters such that this condition holds.

INSERT FIGURE 4 ABOUT HERE
Figure 4 illustrates that if energy prices fall, higher uncertainty increases energy use in both specifications. Uncertainty intensifies the effect of energy price decreases. However, if the price of energy increases the effect of an increase in uncertainty differs between specification I and II. Higher uncertainty intensifies the effect of rising energy prices in specification I, whereas in specification II the effect of rising energy prices is reduced.

7. Estimation results

Our database contains information on cross-sectional units (countries and industries) observed for the period 1978–1996, so we use pooled estimation techniques. We estimate the equations with Generalized Least Squares and use estimated cross-section residual variances to correct for cross-section heteroskedasticity. Testing for common effects versus fixed effects leads us to not reject the null hypothesis of common effects.\textsuperscript{10} Tables 5 and 6 report the common effects estimation results.

\textbf{INSERT TABLES 5 AND 6 ABOUT HERE}

From tables 5 and 6 we draw two major conclusions. First, we find strong evidence for the existence of asymmetric responses of energy use with respect to energy price changes: the relevant coefficients $\mu_k$ and $\gamma_k$ are significant. Second, energy price uncertainty also significantly affects energy use, $\lambda_k$ is significant.

These results imply that the elasticity of energy demand is indeed affected by (i) the direction of changes in energy prices, and (ii) the amount of

\textsuperscript{10} We have also tested whether our results are due to just one or a few industries by means of running industry–specific regressions. The most important coefficients are shown in Appendix C, which indicates that indeed uncertainty does affect the elasticities of energy use in most industries in our data set.
uncertainty decision makers in firms face. Hence, the effectiveness of financial instruments – such as energy taxes – aimed at reducing energy use depends on the level of volatility as perceived by firm managers (and captured here by the one-period ahead forecast of volatility taking into account past changes, as derived from the GARCH regressions in section 4). That means that the results of this analysis provide support for the theory about the impact of uncertainty on the elasticity of energy demand, and hence these results suggest that energy policy models should allow for both uncertainty and the direction of price changes to affect energy demand differently.

However, from a modelling perspective, we need to go one step further, and determine which of the two specifications (I or II) performs best. This step is necessary as multicollinearity prevents the researcher from using the most flexible specification (equations 7 and 8). When using goodness of fit as our decision criterion, we find that specifications (7-II) and (8-II) explain the data better than do specifications (7-I) and (8-I). This indicates that price increases in more uncertain times have a smaller impact on energy use than the same price increases in more stable times, thus indicating that firms tend to postpone investments in energy-saving technologies when times are uncertain. Indeed, the percentage change in energy demand (relative energy demand) equals 

\[ -0.17 + 1.77 Z_t \, (-0.21 + 1.93 Z_t) \] 

when energy prices increase, and

\[ 0.17 + 1.77 Z_t \, (0.21 + 1.93 Z_t) \] 

when prices decrease.\(^{11}\) So, an increase in the price of energy results in a decrease in energy consumed, but this decrease is smaller the more uncertainty an industry faces. On the other hand, if the price of energy decreases, energy use increases more if volatility is high.

Therefore, the regression results of our preferred model indicates that the absolute and relative amount of energy used is less responsive to (relative)

\(^{11}\) It should be noted that average volatility \( Z_t \) in the period 1978-1996 ranges from 0.046 in 1978 to 0.101 in 1990.
energy price increases when the uncertainty an industry faces is higher.\textsuperscript{12} This is consistent with theory, which predicts that the investments needed to achieve a decrease in energy use, are likely to respond more sluggishly to (relative) price changes the larger the potential for price change reversals. However, this effect is not present when considering the response to energy price decreases, as relaxing the constraints on the use of energy does not necessarily require the adoption of new technologies.

8. Conclusions

In this paper we analyze how energy price uncertainty affects energy use. Higher levels of price volatility are likely to render changes in energy use more sluggish, as high volatility implies that there is a probability that energy price change reversals take place, and also that the magnitude of the price change reversal is larger the higher the level of uncertainty. The possibility of adverse price changes makes firms less willing to invest in new technologies (including, for example, energy saving equipment) because investments may turn out to be unprofitable ex–post. Whereas this relationship has been tested in the past, we argue that the uncertainty measure used in this literature (the unconditional standard deviation) is flawed. Using monthly oil price data over the period 1970–2002, we show that price volatility is clustered, and argue that any measure of price uncertainty should take this into account. Volatility clustering implies that high levels of volatility today give rise to the expectation that volatility will remain high in the foreseeable future, and hence the probability of price change reversals is expected to remain high as well. Volatility itself induces firms to respond sluggishly to energy price changes, and this effect is

\textsuperscript{12} To check the robustness of our results, we have tested whether the big spikes in our measure of uncertainty (see the years 1986, 1990, 1994 in figure 3) are responsible for the results obtained above. Including time dummies in the regressions, which are not shown here, shows that the estimates are very robust: uncertainty remains highly significant and the estimates are qualitatively the same.
exacerbated if volatility is clustered over time as higher volatility today then implies that tomorrow volatility is likely to be high too. We therefore construct a new measure of energy price volatility, which takes volatility clustering into account. Our measure is the time–varying conditional variances as obtained by a symmetric GARCH(1,1) model of percentage changes in oil prices. The measure of uncertainty we present is the within–year average conditional standard deviation. In contrast to the standard unconditional standard deviation, the conditional standard deviation as derived from GARCH regressions provides the one-period ahead forecast of volatility taking into account past changes. We test to what extent this measure is able to explain the relationship between energy use, energy price changes and oil price uncertainty. We focus on the price elasticity of energy use and the elasticity of substitution between energy and labor.

We arrive at two major conclusions. First, an increase in energy prices has a relatively small impact on energy use, whereas the impact of a decrease in energy prices is much larger. Second, this asymmetric effect is exacerbated by uncertainty. The higher the price uncertainty, the lower the price elasticity of energy use when prices are increasing, and the higher the price elasticity of energy use when prices are falling. Uncertainty enhances asymmetry as it dampens the effects of increasing energy prices and strengthens the effect of falling energy prices.

Our results thus give support to the theoretical prediction that energy price volatility renders energy–saving technologies less attractive. The policy implications are that in uncertain times, energy taxes are not expected to be very effective in reducing energy use, and that reducing and managing uncertainty should be high up on the policy agenda. Recently, political turmoil seems to increase uncertainty, which leaves us with the second option of managing uncertainty by making economic systems more resilient. These results are
interesting, and underline the relevance of taking energy price uncertainty into account when modeling energy demand, as well as of the necessity to properly measure this uncertainty. However, to fully capture the impact of volatility clustering on investment decisions, a structural model is called for where the estimated GARCH parameters are captured in the agent’s maximization problem. This is left for future research.
References


The oil price series used in this paper is refiner acquisition cost of imported crude oil (US$ per barrel) available on a monthly basis from the Energy Information Administration (http://www.eia.doe.gov/emeu/cabs/chron.html). This series is plotted in figure A1.

INSERT FIGURE A1 ABOUT HERE

The appendix presents a list of the events that have influenced world oil markets and the oil price.


1973–1974
- Oil embargo begins (October 19–20, 1973)
- Oil embargo ends (March 18, 1974)

1979–1985
- Iranian revolution; Shah deposed (January 16, 1979)
- OPEC raises prices 14.5% (April 1, 1979)
- OPEC again raises prices 15% (July 1, 1979)
- Iran takes hostages (November 4, 1979); President Carter halts imports from Iran (November 12, 1979)
- Saudis raise marker crude price from $19/bbl to $26/bbl (December 13, 1979)
• In 1980, Kuwait, Iran, and Libya production cuts drop OPEC oil production to 27 million b/d

• Saudi Light raised to $28/bbl (April 1, 1980), Saudi Light raised to $34/bbl (December 1980)

• First major fighting in Iran–Iraq War (September 23, 1980)

• March 11, 1982 US boycotts Libyan crude

• Libya initiates discounts: non–OPEC output reaches 20 million b/d, OPEC output drops to 15 million b/d (1982)

• OPEC cuts prices by $5/bbl and agrees to 17.5 million b/d output target (1983)

• Norway, United Kingdom, and Nigeria cut prices (October 1984)

• OPEC accord cuts Saudi Light price to $28/bbl (January 1985)

1990–1991

• Iraq invades Kuwait (August 2, 1990)

• Operation Desert Storm begins (January 16, 1991)

• Persian Gulf war ends (February 28, 1991)

1992–1995

• Nigerian oil workers' strike (August–September 1994)

• Extremely cold weather in the US and Europe

1996–2001

• U.S. launches cruise missile attacks into southern Iraq following an Iraqi–supported invasion of Kurdish safe haven areas in northern Iraq (September 5, 1996).

• Prices rise as Iraq's refusal to allow United Nations weapons inspectors into "sensitive" sites raises tensions in the oil–rich Middle East (November 20, 1997).

• OPEC raises its production ceiling (November 29, 1997). This is the first increase in 4 years.
• World oil supply increases by 2.25 million barrels per day in 1997, the largest annual increase since 1988.

• In 1998 oil prices continue to plummet as increased production from Iraq coincides with no growth in Asian oil demand due to the Asian economic crisis and increases in world oil inventories following two unusually warm winters.

• Oil prices triple due to strong world oil demand, OPEC oil production cutbacks, and other factors, including weather and low oil stock levels (January 1999–September 2000).

• Oil prices fall due to weak world demand (largely as a result of economic recession in the United States) and OPEC overproduction (2000).

• Oil prices decline sharply following the September 11, 2001 terrorist attacks on the United States, largely on increased fears of a sharper worldwide economic downturn (and therefore sharply lower oil demand).
Appendix B: OECD dataset

The data used in this paper are derived from the IEA Energy Balances and from the OECD International Sectoral Data Base. Employment is measured in millions of man years; the wage rates are annual wages in thousands of 1990 U.S. dollars. Capital is in billions of 1990 dollars; the rental price of capital is calculated annually using nominal interest rates (government bond rate) and industry-specific deflators and rates of depreciation. Energy is in millions of tons of oil equivalents, and its price is in millions of 1990 U.S. dollars per ton of oil equivalents. Industry-specific energy prices have been derived by summing up the amounts of money spent on each energy carrier (oil, coal, electricity, gas, and other) and by subsequently dividing that by the total amount of energy used. All nominal prices were transformed in real prices using the producer price index of the industry under consideration. Output is also in billions of 1990 U.S. dollars. Currency conversion has been applied by using country- and industry-specific deflators and 1990 Purchasing Power Parities.

INSERT TABLES B1 AND B2 ABOUT HERE


There are nine sectors of industry in our data set: Food, beverages and tobacco (FOD), Textile, wearing apparel and leather industries (TEX), Wood and wood products (incl. Furniture; WOD), Paper and paper products, printing and publishing (PAP), Non–metallic mineral products (except products of petroleum and coal; NMM), Basic metal industries (BMI), Metal products (excluding
machinery and transport equipment: BMA), Transport equipment (MTR), and Construction (CST).

We have fifteen countries: Australia (AUS), Belgium (BEL), Canada (CAN), Germany (DEU, from 1990 onwards), Denmark (DNK), Finland (FIN), France (FRA), United Kingdom (GBR), Italy (ITA), Japan (JAP), the Netherlands (NLD), Norway (NOR), Sweden (SWE), United States of America (USA) and Western Germany (WGR, until 1990).

We have an unbalanced panel since not all series are available for all countries. For instance, for Germany and Australia we only have data for construction. All other countries and sectors are well represented in our database.
Appendix C: Sectoral results

If we estimate models 7–II and 8–II for each industry separately, we find that our conditional volatility measure contributes to explaining percentage changes in (relative) energy use in most industries. The exceptions are Construction (CST), Non–metallic mineral products (petroleum and coal products not included; NMM), and Wood and wood products (including Furniture; WOD). The industry–specific estimation results are summarized in table C1.

INSERT TABLE C1 ABOUT HERE