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Induced Innovation and Relavtive Factor Share

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Abstract

We build up an induced innovation model based on Popp's article in AER, 2002. His model measured the effect of energy prices on energy-efficient innovations. Using the relative factor shares of energy and labor instead of the energy prices per se, we are able to explain the patenting activity in a better way. Also, with the combination of theoretical and empirical research, we can prove that technological change of energy is related with prices and quantities of both energy factor and labor factor. Furthermore, we discuss on the possibility of the hypothesis of diminishing returns to knowledge, which reveals that diminishing returns are not necessary to exist in the induced innovation model. The result we got is not very strong but it shows more elasticity than Popp’s model.

Key words: induced innovation, relative factor share, energy price, diminishing returns to knowledge, patent citations.

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1 Introduction

Innovations of energy-saving technology have increased enormously during recent decades, for many reasons. One of these could be the energy crisis of 1970s which affected energy prices, another could be the introduction of environmental policies such as emission abatements and environmental taxes. Furthermore, the accumulated knowledge stocks could be another factor affecting innovation rates on energy.

In recent research, a lot of efforts have been made to find out the relationship between energy-saving technological change and economic policies.[1] Out of which, the hypothesis of induced innovation is frequently cited— *"a change in the relative prices of the factors of production is itself a spur to invention, and to invention of a particular kind—directed to economizing the use of a factor which has become relatively expensive"* (Hicks, 1932, pp.124–125), which suggests that an increase in real energy price will induce energy-saving innovation. Many authors have since tried to model this relationship, but the major breakthrough came with Acemoglu (2002). Acemoglu proposed a model and developed the theory of directed technological change. Turning to empirical research, the contribution made by Popp (2002) is most important, because he successfully modeled the relationship between energy prices and technological change using the citation of patents as endogenous variables.[2]

In Popp's analysis, the induced innovation is related to not only real energy prices but also usefulness of existing knowledge. He used patent citations from 1950 to 1994 to construct a weighted series of "knowledge stocks" of 11 energy sectors, with which he formulated the model. The results showed that both the energy prices and knowledge stocks have a strongly positive impact on new technological change, which implies that we can encourage more energy-saving

[1] The existing literature includes Smulders and de Nooij (2003), Grimaud and Rouge (2008), Goulder and Schneider (1999).

[2] Other empirical work see for instance Jaffe and Trajtenberg (1996) and Newell et al. (1999).

innovations by using environmental taxes and regulations, and also using the technology per se. But in his paper he also found that there are diminishing returns to knowledge in energy research, which we would discuss carefully in our thesis.

However, some theoretical researchers indicate that it is not the real price but relative factor share we should take into consideration (Hart, 2011). Since the patent regressand is a proportion of total patents of each year (Popp, 2002), we should also look at the impact of other factors such as labor, so that we may get a more valid model to use.

This thesis is based on the model which Popp used. However, we change the specification to make it consistent with theory, considering the impact of the factor of labor. In other words, we will use the Popp model while using relative factor share of energy and labor instead of energy price only. More specification will be illustrated afterwards.

The rest of the thesis is organized as follows. In Section 2 we will put more efforts on theoretical and empirical specification of our model. In Section 3 we further illustrate the model and data, Section 4 and Section 5 are the regression results and conclusion respectively.

2 Theoretical Specification and Popp Model

Popp used a log–log model to describe the relationship between the successful patent applications and energy prices, a knowledge stock and other variables such as the government R&D expenditure. In this kind of model, the coefficients estimated could be interpreted usefully as elasticities of the explanatory variables, which is a good tool for the policy makers. What should be noted is that as for the energy prices and government R&D he took an adaptive expectations model with distributed lags which is more realistic and sophisticated than using the raw data of energy prices and government expenditures, considering the real world situation. The Popp model is shown as follows:

$$\log\left(\frac{EPAT_{i,t}}{TOTPAT_t}\right) = \phi_i + \gamma(1-\lambda)\log P^*_{E,t} + \theta \log K_{i,t-1} \quad (1)$$

$$+ \eta(1-\lambda)\log Z^*_{i,t} + \lambda^t \mu^0 + \varepsilon_{it},$$

$$i = 1,\ldots,11; t = 1,\ldots,20$$

where

$$P^*_{E,t} = P_{E,t} + \lambda P_{E,t-1} + \lambda^2 P_{E,t-2} + \cdots + \lambda^{t-1} P_{E,1}, \quad (2)$$

and

$$Z^*_{i,t} = Z_{i,t} + \lambda Z_{i,t-1} + \lambda^2 Z_{i,t-2} + \cdots + \lambda^{t-1} Z_{i,1}. \quad (3)$$

$EPAT_{i,t}$ represents the number of successful nongovernment U.S. patent applications for technology field i in year t, and $TOTPAT_t$, represents the total number of successful nongovernment U.S. patent applications in the same year. $P_{E,t}$ is the price of energy in that year. The variable $K_{i,t-1}$ represents the stock of knowledge that had accumulated by the previous year, and should be thought of as the knowledge available to the researcher at time t. Values for this stock will be introduced later. Z is a vector of the other independent variables such as R&D spending by the U.S. Department of Energy.[3]

The interpretation of parameters is consistent with the theory of Koyck approach (Koyck, 1954). As we can see, the energy price is using an adaptive expectations model where λ is known as the coefficient of expectation, which stands for the weight put on the past observations. Note that $0 < \lambda \leq 1$. The term $\gamma(1-\lambda)$ represents the short-run price elasticity of energy technological change where γ is the long-run elasticity and $(1-\lambda)$ could be seen as weight without all past impacts. And μ^0 is the truncation remainder.

Popp's model is ground-breaking. Since Hicks (1932) researchers have struggled to establish empirical relations on policy-induced development of technological change with respect to the process per se. Hence most models on the

[3]These describes of variables are taken from Popp (2002).

policy have taken technology as exogenous. Popp did a good job on induced innovation hypothesis. He successfully quantified knowledge to take knowledge endogenously as explanatory variable. However, theoretical researchers suggest that other explanatory variables should be built into the model in order to be valid.

From the theoretical model of Acemoglu (2002) we can get Equation 4 and Equation 5 for different factors L and Z:

$$\dot{N}_L = \eta_L N_L^{(1+\delta)/2} N_Z^{(1-\delta)/2} S_L, \tag{4}$$

and

$$\dot{N}_Z = \eta_Z N_L^{(1-\delta)/2} N_Z^{(1+\delta)/2} S_Z, \tag{5}$$

where $\delta \leq 1$ is the degree of state independence, η_L and η_Z are positive parameters, and S_L and S_Z are investment levels for factors L and Z respectively. When $\delta = 0$, it implies N_L and N_Z create spillovers, with the same weight of 0.5, for the current research in both sectors. In contrast, when $\delta = 1$, then the research in factor L is irrelative with factor Z, which suggests that there are no spillovers between sectors. We can transform these equations into time series model according to the work of Hart (2011). And we can see the links between the two expressions. The term K_a corresponds to N_L while K_b corresponds to N_Z. I_a is the investment of factor a which is equal to S_L in Equation 4, and the same applied for I_b and S_Z. Note that $\sigma = 1 - \delta$. And the coefficients $\eta_L = r_a^{-1}$ and $\eta_Z = r_b^{-1}$.

$$K_{at+1} - K_{at} = K_{at}^{1-\frac{\sigma}{2}} K_{bt}^{\frac{\sigma}{2}} I_{at+1}^{\phi} / r_a, \tag{6}$$

and

$$K_{bt+1} - K_{bt} = K_{bt}^{1-\frac{\sigma}{2}} K_{at}^{\frac{\sigma}{2}} I_{bt+1}^{\phi} / r_b. \tag{7}$$

Here K_{at} and K_{bt} are current knowledge level at period $t+1$ of factor a and b respectively , I_a and I_b are inputs, r_a and r_a are positive parameters, and ϕ,

σ are both parameters between 0 and 1. The term ϕ generalized the situation of investment, where in Acemoglu's model $\phi = 1$ is the special case. These functions imply that general knowledge of one factor based on its input can be augmented by both knowledge inside this factor and spillovers. They also suggest that we can build up a relationship between technological change and previous knowledge stocks and also the factor input. If we take the ratio of Equation 6 and 7, we will derive such relation as follows:

$$\frac{K_{at+1} - K_{at}}{K_{bt+1} - K_{bt}} = A \left(\frac{I_{at+1}}{I_{bt+1}} \right)^{\phi} \left(\frac{K_{at}}{K_{bt}} \right)^{1-\sigma} \tag{8}$$

In Equation 8 we can see that it is similar to Popp's model, in which $EPAT_{i,t}$ could be represented by a and $TOTPAT_t$ is replaced by b, and other determinants such as government R&D are omitted for simplification.[4]

And we also define that

$$S = \frac{I_a}{I_b} = \frac{P_a Q_a}{P_b Q_b}, \tag{9}$$

where S is the relative factor share of a and b, or, the ratio of factor share of a and b. The size of S is determined by the price and quantity of both factor a and b. Then we take the log of Equation 8 and replace I_a/I_b with S. The derived equation gives our primary model of this thesis:

$$\log \left(\frac{K_{at} - K_{at-1}}{K_{bt} - K_{bt-1}} \right) = \alpha + \phi \log S_t + \theta_1 \log K_{a,t-1} + \theta_2 \log K_{b,t-1} + \cdots \tag{10}$$

Note that θ_1 and θ_2 in Equation 10 are basically the same parameters with the absolute value of $(1 - \sigma)$ and opposite signs. We will discuss the model more in Section 3.4.

From Figure 1 we can get intuitive information about the patent activity and the other two explanatory variables we use in this thesis. They are all normalized to be 1 in the year 1970. The curve of relative factor share is defined by SE/SL which is the ratio of energy factor share and labor factor share. We can observe that curves of relative factor share and energy price are

[4] We can also add Z_i in Equation 6 and 7, then it will be consistent with Popp's Model.

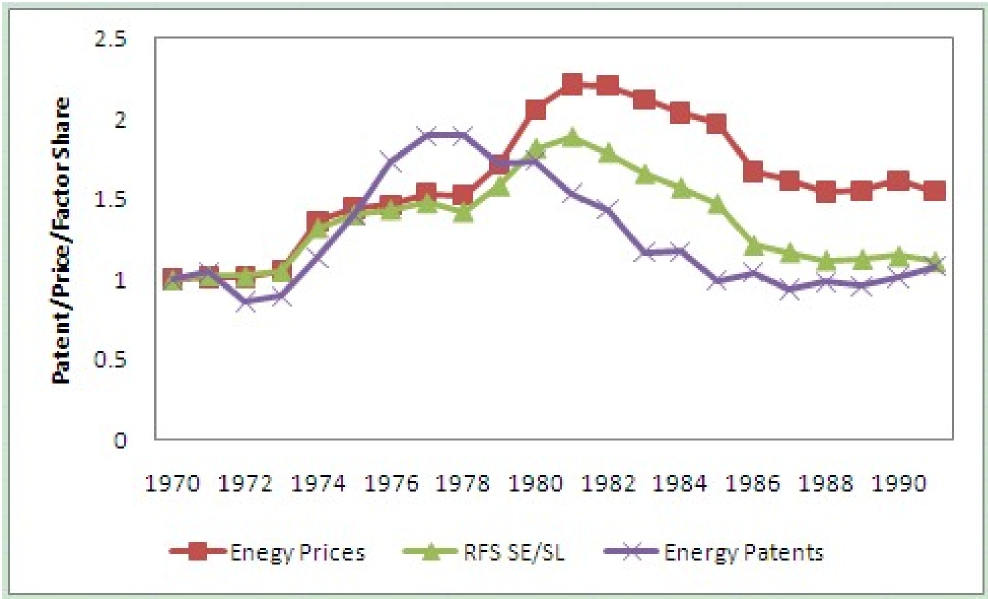

Figure 1: Energy Patents, Energy Prices and Relative factor Share

fundamentally following the same shape at the beginning, but diverge at around 1976. One of the reasons could be the denominator of the ratio of factor share which is the factor share of labor, is increasing over time. So that it brings down the trend of relative factor share compared to the trend of energy price. Another could be the quantity of energy is decreasing due to the energy-saving innovations. Both of the impacts make the trend of factor shares increase more slowly than the trend of real energy prices.

The figure suggests that if energy prices can explain the variation of patent activity, then factor share can be a good explanatory variable too, if not even better. Note that the patenting activity peaked at around 1977 while energy prices kept increasing until 1981. Popp explains that this is because there exists diminishing returns to knowledge. Hence the knowledge begins declining before the prices start to fall. However, if Popp is correct about the diminishing returns, and also the coefficient of energy prices is significantly positive in his model as he demonstrated, then it cannot be explained that when the real prices decreased after 1981, the patents did not decline even faster. Moreover, when the real prices stayed relative constant in the last few years, the patents did not keep declining but leveled off. So we can make some guess that Popp's model might not reflect the reality.

3 Data and Model

3.1 Data

Before we go into the regression of our model, we will make some explanations about data first. Thanks for the generous help of David Popp, we are provided most of the raw data taken from his research directly, which are real energy prices[5] and U.S. nongovernment patents from 1971 to 1991. Besides, there is more patent data from 1950 to 1994 used to build the knowledge stocks.[6] In order to avoid zero citations of most values, Popp divided these patents into 11 different sectors,[7] including 6 energy supply technology groups and 5 of demand. We also use such classification in our thesis. Other data for labor comes from the US Bureau of Economic Analysis National Accounts.[8] What should be noticed is that the index used to measure the real price of labor is different from the previous study, so we did some transformations to better fit the model in getting the factor share.

[5] The prices are in constant 1987 dollars which is deflated by a GDP deflator.

[6] More information about the energy patent data set please see Popp (2002) pp.161-165.

[7] The 11 sectors are Coal liquefaction, Coal gasification, Solar energy, Solar batteries, Fuel cells, Waste as fuel, Waste heat, Heat exchange: general, Heat pumps, Stirling engine, Continuous casting, which are represented by $i = 1, \cdots, 11$ respectively.

[8] http://www.bea.gov/national/nipaweb/SelectTable.asp and for GDP, together with energy related data is from http://www.eia.gov/totalenergy/data/annual/index.cfm. (Look under Energy Overview to find the relevant data)

3.2 Forming the Knowledge Stocks

The essence of the Popp model is the construction of knowledge stocks. Since we do not have database of what Popp has produced, we produce the productivity estimates by using his methodology. Here we will demonstrate how to derive the productivity estimates and knowledge stocks. Using the model introduced by Jaffe and Trajtenberg (1996) and developed by Popp (2002), we can get probability of citations. The reason why we use probability instead of the raw number is that we can eliminate the effect of the total patents followed. The equation of the probability of citation is :

$$P_{i,CTD,CTG} = \frac{c_{i,CTD,CTG}}{(n_{i,CTD})(n_{i,CTG})}, \tag{11}$$

where $P_{i,CTD,CTG}$ is the probability of the citations of patents granted in year CTD and applied by the year CTG in sector i, the numerator c is the number of citations and n is the number of patents in the granted year and application year respectively. In order to estimate the productivity parameters Popp developed the model as follows:

$$\begin{aligned} P_{i,CTD,CTG} =& \alpha_i \alpha_{i,CTD} \alpha_{CTG} \exp[-\beta_1(CTG - CTD)] \\ & \times \{1 - \exp[-\beta_2(CTG - CTD)]\} + \varepsilon_{i,CTD,CTG}. \end{aligned} \tag{12}$$

In Equation 12, CTG means the citing year of new patent applications, while CTD refers to the year of existing patent being cited. The coefficients β_1 stands for the decay of knowledge and β_2 is the rate of new knowledge diffusing into society. Equation 12 also presents some weights on the process of citation, which are α_i, $\alpha_{i,CTD}$ and α_{CTG} respectively.

Out of the three parameters, $\alpha_{i,CTD}$ is most valuable in our analysis. It is the "usefulness of the knowledge represented in the patent being cited".[9]

[9]The parameter α_i stands for the frequency of citations within each technology group, and α_{CTG} is the frequency with which patents applied for in the citing year cite earlier patents. Detailed explanation for the two parameters can be found in Popp (2002).

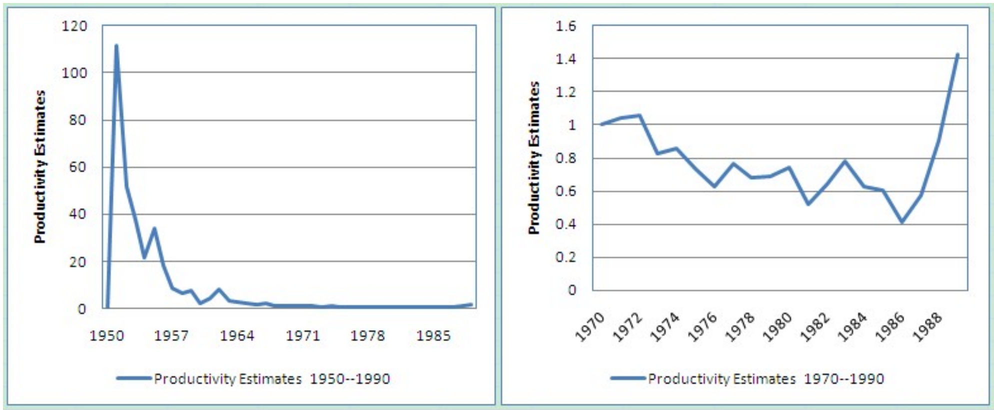

Figure 2: Figure shows the productivity estimates ($\alpha_{i,CTD}$) of coal liquefaction. The left figure presents the estimates trend from 1950s, while the right one focuses on the period between 1970 to 1990, which highlights the effect of energy crisis of 1970s.

This means the likelihood of the patent granted in the cited year will be cited by the following patent applications. In this sense, the higher value of the parameter, the more valuable the patent is. For instance, if $\alpha_{11,1970} = 1$, we could say that the productivity of patent cited in 1970 of continuous casting is standardized to be 1, and any patent with the $\alpha_{i,CTD}$ greater than 1 is more valuable and productive than the former, and vice versa. These parameters are called "productivity parameters". In the estimation observations are weighted by $(n_{CTD} * n_{CTG})^{0.5}$ to avoid problems of heteroskedasticity (Greene (2003)).

In Figure 2 we can see some principles derived from the formulation of productivity estimates. Those estimates show a declining trend in the long-run, Popp explained that it was because there exists a diminishing return to the knowledge. From the figure we can observe that the values peak around 1950,[10] which means the patents granted around 1950s are most likely to be cited by subsequent patents. Considering the parameter in 1970 is normalized to be 1,

[10]The reason of zero value of 1950 will be discussed in next subsection.

the estimate of 1951 is 111.68 which suggests that knowledge in 1951 is much more valuable than that in 1970 and afterwards. Even after controlling some effect such as opportunities to be cited, the old patents still outweigh the new ones. We would speculate that the model overvalued the old knowledge, because the frequency of being cited is only an aspect of being "useful". Furthermore, if we take the spillovers between knowledge into consideration, the technological change in other fields such as communications and transportation will affect both the demand and supply side of energy, but this is beyond the discussion of our framework. However, the estimating results support Popp with diminishing returns to knowledge in the scope of patent stocks weighted by citations.

Popp used these estimates to form the knowledge stocks for each sector. The formulation of knowledge stocks weighted by productivity estimates[11] is:

$$\begin{aligned} K_{i,t} &= \sum_{s=0}^{t} \alpha_{i,CTD} PAT_{i,s} \exp[-\beta_1(t-s)] \\ &\quad \times \{1 - \exp[-\beta_2(t-s)]\}. \end{aligned} \tag{13}$$

Here $\alpha_{i,CTD}$ is the same as we explained before, $PAT_{i,s}$ is the patent granted in the cited year, $(t-s)$ refers to the lag between the citing year and cited year, and β_1 and β_2 are rates of decay and diffusion respectively.

Figure 3 plots two of the knowledge stocks we derived from this model. It is for the sector of coal liquefaction and waste fuel from the year 1970 to 1990. We can see from the figure that in both sectors of energy the unweighted knowledge stocks keep increasing over time, while the weighted one performs differently. Popp declared that in most sectors the weighted knowledge stocks tend to fall over time, but considering the potential bias on the weights of old knowledge, it is not hard to derive such relationship. In addition, the downward trend does not

[11] The knowledge stocks build without the productivity estimates can also be found in Popp (2002), which we do not apply because the weighted one performs better in the regression. Readers with interest are referred to Popp (2002), which includes discussion for both weighted and unweighted patent stocks.

Figure 3: Figure shows the weighted ($K_{i,t}$) and unweighted knowledge stocks for coal liquefaction and waste fuel. Note that the former presents some trend of diminishing returns while the latter does not.

seem that obvious, and even some sectors[12] experience an upswing at the end of the 1980s. And empirical research on the diminishing returns also showed some contradictory results, especially when taking all patents into account. It shows that the diminishing returns only exist within narrowly defined technology fields and the returns to research vary across different areas (Popp, 1998).

3.3 Insufficiency of the Data

Although we did use the same methodology and data from Popp model, there are still some insufficiencies in the data we processed. Note that in order to simplify our regression, some minor adjustments are made according to these insufficiencies, but the logic and principle are not changed much.

1. About the productivity coefficients we estimated, there are 9 of them which turn out to be non-significantly different from 0. But the difference is minor—just 9 out of 460 estimates—and we got really good results with the adjusted R-squared of 0.699, which is closed to the original regression

[12]We can see the waste fuel as shown in Figure 3 for example.

results of Popp did, about 0.755 correspondingly. Apart from that, all estimates of the dummies for citing years and technology groups work very well. Furthermore, the figures derived from the productivity estimates and knowledge stocks followed show the same curves for each sector. So we take the results as reliable data for the further study.

The reason why it returns zero value of the estimates can be explained from the definition of productivity parameters. Since the productivity estimate is an indicator of the usefulness of the patent cited, we would expect some patents for a certain year in a certain sector to contribute little to the following patent applications. The contribution was so small that it is not significantly different from zero, so we can just ignore it when constructing the knowledge stocks. In fact, most patents granted do not have the chance to be cited by the future applications. Although Popp tried to avoid such problems by dividing them into larger classifications, the possibility of zero citation remains. But it won't affect the relationship we try to capture.

2. When we process the data of patents for the dependent variable, we are supposed to count out the patent assigned to the government, in order to control the effect of government activity. But unfortunately, some unusual values show that the number of patents granted in sector of heat pumps is negative in certain years, which is not reasonable. Since we got the data from Popp and we want to keep the consistency of the data source, we decided to replace the negative values with 0.001 which can be contemporaneously reported in the regression of a log–log model. For improvement, we had better to check the original sources of the data in future study.

3. The Z_i part of Popp's model refers to some aspects to control for other variables, such as R&D spending by the U.S. Department of Energy and

some technology-specific variables. However, when putting these variables into model, Popp reported that they were not significant. So we drop this part for simplification.

3.4 Modeling

Recall that the aim of this thesis is to analyze the relationship between technological change and the relative factor share in the light of theory in Section 2. So we choose energy and labor as our object of study, in order to find out some relationship between the directed technological change and the relative factor share of energy and labor. Recall the theoretical model of Equation 10 in Section 2. We develop the model in the form as below:

$$\log\left(\frac{EPAT_{i,t}}{LPAT_t}\right) = \phi_i + \gamma(1-\lambda)\log S_t^* + \theta_1 \log K_{i,t-1}^E \qquad (14)$$
$$+\theta_2 \log K_{L,t-1} + \lambda^t \mu^0 + \varepsilon_{it},$$

But we do not have the data of the labor patent, and technological change in labor is also difficult to capture by using the same principle as energy. If we choose an exponential growth rate for the labor technological change then the left hand side of Equation 14 will be just energy, which includes less information than we need.[13] So we use the same definition of dependent variable in Popp's model, and choose the total patents as a proxy for the labor patent. This is because theoretical research suggests there is the long-run stability of factor shares for labor (Acemoglu (2003)). It indicates that the factor share of labor takes a constant proportion of production in the long-run. So we assume labor patents as a steady proportion of the total economy in patenting activities. Besides, we can still benefit from the definition without the effects of "growth in the economy and exogenous changes in patenting behavior". Furthermore, the knowledge stocks for labor can not be constructed in the same reason, so we assume that knowledge stocks for labor is constant over time.

[13] Because patenting in labor will be constant after taken log.

Thus, after the adjustment of dependent variable as well as the assumption of constant knowledge stocks for labor, we get our regression model as shown:

$$\log\left(\frac{EPAT_{i,t}}{TOTPAT_t}\right) = \phi_i + \gamma(1-\lambda)\log S_t^* + \theta\log K_{i,t-1} + \lambda^t\mu^0 + \varepsilon_{it}, \quad i = 1,\ldots,11; t = 1,\ldots,20 \tag{15}$$

where

$$S_t^* = S_t + \lambda S_{t-1} + \lambda^2 S_{t-2} + \cdots + \lambda^{t-1}S_1. \tag{16}$$

Here the model for the relative factor share is using an distributed lag model to be consistent with the an adaptive expectation of it. The parameters chosen are the same as Popp's model for the purpose of comparison.[14]

4 Empirical Applications and Results

The models with respect to energy prices and relative factor shares are using the form of adaptive expectation model, where λ is the coefficient of finite distributed lag terms. We cannot use OLS method to estimate the relationship, because "if an explanatory variable in a regression model is correlated with the stochastic disturbance term, the OLS estimators are not only biased but also not even consistent; that is, even if the sample size is increased indefinitely, the estimators do not approximate their true population value" (Gujarati, 2003, pp. 677). Therefore, we turn to transform Equation 15 and 16 into a Partial Adjustment Model (PAM) to get an unbiased estimation, which is displayed as follows:

$$Y_t = \phi(1-\lambda) + \lambda Y_{t-1} + \beta X_t + \theta(Z_t - \lambda Z_{t-1}) + \nu_t. \tag{17}$$

Note that such transformation can be found in Gujarati (2003) and we use infinite lags for the explanatory variables P and S, so there will not be truncation

[14] Explanations for parameters can be seen at Section 2.

remainder left. Y is the dependent variable which is $\log(EPAT_{i,t}/TOTPAT_t)$ in our case, where X refers to the logged energy prices or logged relative factor shares in different regressions, and Z stands for lagged knowledge stocks for energy after taken log.[15] The parameters are mostly with the same meaning as Equation 15 but β here is $\gamma(1-\lambda)$ and ν_t is a moving average of ε_t and ε_{t-1}.

We postulate the hypothesis of PAM, then we derive the following equation by shifting one period and timing by ρ, which is the autocorrelation coefficient. In this way we can cancel out the effect of autocorrelations.

$$\rho Y_{t-1} = \rho\phi(1-\lambda) + \rho\lambda Y_{t-2} + \rho\beta X_{t-1} + \rho\theta(Z_{t-1} - \lambda Z_{t-2}) + \rho\nu_{t-1}. \tag{18}$$

In Equation 18, ρ is coefficient of adjustment. It can be taken as the correlation coefficient between Y_t and Y_{t-1}. And if we take the difference of Equation 17 and 18, then we get following relations without the effect of autocorrelation:

$$\begin{aligned} Y_t - \rho Y_{t-1} = \phi(1-\lambda)(1-\rho) + \lambda(Y_{t-1} - \rho Y_{t-2}) + \beta(X_t - \rho X_{t-1}) \\ + \theta(Z_t - \lambda Z_{t-1} - \rho Z_{t-1} + \rho\lambda Z_{t-2}). \end{aligned} \tag{19}$$

Hence, we estimate Equation 19 as a solution of distributed lags of price and factor share. Unfortunately, the results show that ρ is not significantly different from zero which means no convincing results are given by such estimation. Therefore, we estimate Equation 17 instead.

Table 1 presents the results from the regressions using energy prices and relative factor share as explanatory variables respectively. Short-run elasticities for each variable are shown with t-statistics for each coefficient in parentheses. The first column is for regression on adaptive expectation of energy price, which is Popp's specification. And the second one is our model which is presented in Equation 15. Since we apply the infinite lags assumption, the truncation remainder is not reported at all.

From Table 1 we can see that in both cases the lagged knowledge stocks are playing a significant role in the model. The short-run elasticity of the knowledge

[15] Note that Z_t is for lagged knowledge stocks whereas Z_{t-1} is for that of two years lag.

Table 1: Induced Innovation Regression

Independent Variables	Energy Price	Relative Factor Share
Constant ϕ_i	-3.842	-1.813
	(-3.081)	(-1.719)
Weight on past observations λ	0.750	0.744
	(-13.131)	(-13.401)
Energy prices and relative	0.063	0.246
factor share $\gamma(1-\lambda)$	(-0.396)	(-1.505)
Lagged knowledge stocks θ	0.794	0.805
	(-5.979)	(6.227)
Long-run elasticity γ	0.254	0.961
Median lag	2.41	2.34
Mean lag	3.01	2.90
Number of technology groups	11	11

stocks in Popp's model is 0.794, which is closed to our model 0.805. Both estimates suggest that the construction of knowledge stocks using patent citations is acceptable in estimating the induced innovation. Also, the parameters of λ are both significant and consistent, which suggest that the median lag range from 2.34 to 2.41. Verbally, half of the total change in patenting activity is accomplished in around 2.4 years, which is quite reasonable. However, regression results show that neither Popp's model nor ours performs very well under our assumptions. The estimate of energy price is not significantly different from zero with a t-value of only about -0.396, which we cannot accept. Similarly, estimate of relative factor share is not significant enough, although it shows a little improvement than the former, with a t-statistics of 1.505, which is almost at the border of confidence interval.[16] If we compare our results with Popp's, we find that even though Popp's result is more significant than ours, the size of coefficient of energy price is the same. This suggests that if we accept our result of relative factor share at a certain significant level, then the effect of relative factor share is larger than the energy prices in inducing innovations. 1% of change in energy prices could only affect the patenting activity by 0.06%, but if the relative factor share changes 1%, the change in innovation would be 0.246%, almost four times larger than the prices.

Nevertheless, we did further study in this framework by taking both prices and factor shares into consideration. Thus,

$$Y_t = \phi(1 - \lambda) + \lambda Y_{t-1} + \beta_1 X_t + \beta_2 S_t + \theta(Z_t - \lambda Z_{t-1}) + \nu_t. \tag{20}$$

Here X and S are logged energy prices and logged relative factor shares respectively, and β_1 and β_2 are short-run elasticities accordingly. Regression results are presented in Table 2. From the table we observe that λ and parameter for knowledge are basically remain the same as the former regression, but performances of two explanatory variables are apparently different. The estimate of

[16] The P-value of relative factor share is about 0.132, if we assume a significant level of 15%, we can accept it.

factor shares is significant as theory suggests, while on the contrary, not only the t-statistics of price is not significant as noticed previously, but also the sign of the coefficient is negative.

Table 2: Regression on Both Energy Prices and Relative Factor Share

Independent Variables	Estimates
Constant $\phi(1-\lambda)$	2.141
	(0.503)
weight on past λ	0.751
	(13.149)
Relative factor share β_2	0.500
	(1.762)
Energy price β_1	-0.287
	(-1.044)
Lagged knowledge stock θ	0.814
	(5.994)

These results shed a little light on the relation between relative factor shares and induced innovation, especially when taking the energy prices as comparison. Recall the discussion we had in Section 2 and Section 3.2, if the relative factor share of energy and labor better captures the induced innovation, then the patenting activity may be less, if not the least, affected by the hypothesis of diminishing returns to knowledge. Popp has assumed that "the cumulative effect of diminishing returns over time helps contribute to the quick fall in energy patenting activity". So if we prove that the patenting activity can be explained by the variable of the relative factor shares, then the increasing factor shares for labor over time would be another aspect that affects patenting. These relations dampen the assumption of diminishing returns to knowledge. Even such hypothesis may hold true, its effect is not as large as it was thought to be by Popp.

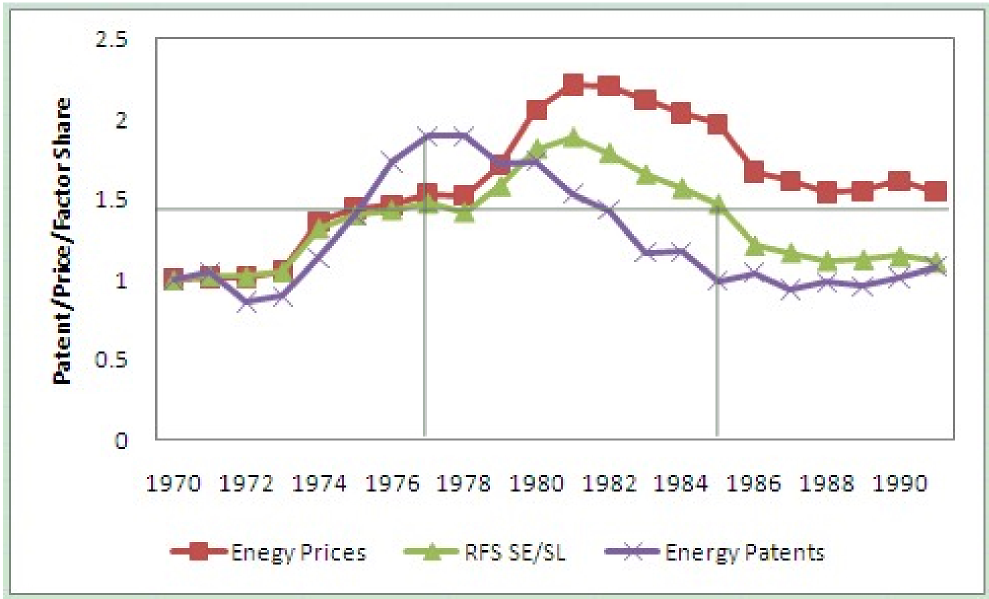

Figure 4: Patenting Activities with Auxiliary Lines

The model consists of both factors of energy and labor, so that it reveals the potential relation of induced technological change and other primary factors. Recall the curves of Figure 1, the increase in relative factor shares gives rise to the energy-saving innovations. But the increasing labor factor share and the economizing of energy use will lead to a downward trend of the relative factor shares. Then the patenting activities are brought down by the factor shares. The relative factor shares are more reasonable in the model than prices did because they can be seen as a weight put on energy prices so that they better explain the declining trend of innovations other than diminishing returns to knowledge. This illustration can be observed in Figure 4. We can see that the curve of relative factor shares better captures the shape of innovations than energy prices. This could be another way of interpreting why there may not be the diminishing returns to knowledge.

The reason why the regressions are not significant in some variables can be explained in several ways. One of them is the endogeneity of the model.

Another reason could be that we should take finite lags as model for prices and factor shares because an infinite series of past values is not possibly observed. Furthermore, the autocorrelations existing in the model put on more difficulty to be regressed. One of the way out considering autocorrelation is to use Generalized Method of Moments (GMM). GMM allows for correlation between error term and explanatory variables and corrects the results for autocorrelation. Moreover, recall that we dropped the R&D expenditure and other exogenous variables for simplification in our specification. Although they are not significant in Popp's model, we should still take them into account in order to get other variables significant. These should be noted in further studies.

5 Conclusions

In this thesis we discuss the Popp model and our specification based on it in the light of theoretical research of technological changes. We also discuss the possibility of the hypothesis of diminishing returns to knowledge which Popp strongly suggested. Although there exists insufficiency in our regression, we can still shed some light on relationship between induced innovation and relative factor shares of energy and labor. The major result is that, with the same specification of other variables in the model, relative factor share performs better than price per se. That is because the relative factor shares do not only consider the impact of real energy prices but also take other factors such as increasing real wages and quantities of energy and labor into consideration, where factor share of labor can be visualized as weight of energy prices so that it tilts the effect of prices on patenting activity. The results we get is not as strong as Popp's, but we find the explanatory variable we used is more promising than Popp's. The elasticity of relative factor shares is much larger than the price elasticity. And this means the relative factor share explains more than energy in the induced innovation theory.

Another speculation derived from this result is that even though the possibility of diminishing returns to knowledge exists, it does not necessarily mean that the diminishing returns play a large part in the patenting activities. Popp may overvalue the productivity parameters which suggest old knowledge is much more useful than the new one, as well as its importance in induced innovation theory. The construction of knowledge stocks derived from higher value of previous knowledge could give a downward trend over time. However, such trend is not obviously significant nor even consistent within all technological groups. In addition, according to other literature, the diminishing returns cannot be generalized.

A follow-up research would involve the separation of prices and quantities of energy and labor. Because energy and labor could perform differently in the decision-making process of forms in the short-run. It also has to be noted that the results are not statistically convincing although they provide some light in the direction. Improvement can be done in such ways. First of all, take account of all exogenous variables as Popp suggested. Secondly, research should be done on how to formulate the labor productivity in an appropriate way. Finally, use the GMM method and take finite lags of prices or relative factor shares. Future work should be focused on the improvements.

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