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Abstract

Directed technological change is very important, since it determines (for instance) the rate of resource exploitation. The long term relationship between resource prices and demand needs to be understood better, in the light of new theories which have been developed to a great extent by Acemoglu; in Acemoglu's model, there either exists a balanced growth path (complements) or a corner solution is approached (substitutes), depending on the elasticity of substitution. In this thesis the elasticity of substitution between labour and metals as well as between aluminium and iron is estimated by OLS regression using a CES production function and the Nerlove model. The relative factor shares are examined. The former two are suggested to be substitutes, the latter ones complements. This is surprising, it can however be explained by the use of aggregate data which will show the total sum of factor relations over all sectors. In further work it would be interesting to limit the analysis to one economic sector; alternatively, existing models need to be improved in order to reflect changing sector sizes.

Contents

1 Introduction

The ongoing discussion about climate change, emission and pollution reduction within countries and among members of the international community needs to be brought forward by clear policy recommendations. There are two goals many policy makers strive for: ongoing economic growth, and pollution levels that do not exceed the nature's ability to recover from human intervention. The type and speed of resource exploitation is thus crucial and depends greatly on available technologies, prices and demand.

Resource demand curves depend on the available technologies, which in turn depend on prices in the long run. Whenever a price trend changes one expects the trend of the demand curve to change, too. Therefore, it is not good enough to only extrapolate price trends. It is rather necessary to understand the long term relationship between prices and demand for resources, linked to directed technological change. The theoretical literature on directed technological change mainly focuses on the two factors skilled and unskilled labour, but the ideas and methods are just as well applicable to resources and labour or capital. This has however hardly been done so far. The empirical literature on resources focuses almost entirely on prices without directed technological change (exception: Smulders, de Nooij [16]). There is hardly any literature to be found analysing prices in conjunction with quantities, in an economic context including directed technological change.

The aim of this paper is to evaluate data on both resource prices and consumption in the light of theories of directed technological change, and to draw conclusions about possible future trends. The prices and quantities of resources will be analysed, and it is empirically tested if the real world data can be explained by the latest accomplishments in directed technological change theory.

First of all, however, a brief look shall be taken at the relevant literature. The international debate about climate change and possibilities to reduce it has grown immensely during the last decades, greatly stirred also by the Stern report published in 2006 [18], and the initiatives to find follow-up agreements for the Kyoto protocol. Some economists have since tried to shed light on the necessary policy measures that can push innovations towards an environmentally friendly direction, for example by estimating development paths for renewable and non-renewable energy costs (Chakravorty) or by empirically testing the innovation hypothesis (Popp). The induced innovation hypothesis itself, which states that a relative price increase of one production factor will induce innovations in order to scale down the need for this factor, is as old as from 1932 and was proposed by Hicks [9].

Popp analysed in 2002 [14] the relationship between energy prices and the relative amount of energy-efficient innovations while taking into account endogenously formed knowledge stocks. He uses data of energy patents for a time span of 25 years and finds that

> "both energy prices and the quality of existing knowledge have strongly significant positive effects on innovation" (Popp 2002).

His model assumes knowledge stocks only as a fraction of the knowledge accumulated in the past within in the same sector.

Another article looking for possible environmental policies linked to technological change was written in 1997 by Chakravorty et al. [4], "Endogenous substitution among energy resources and global warming". Having in mind the projections by the Intergovernmental Panel on Climate Change (IPCC), they estimated the extend of global warming and the future use of different energy sources under a variety of scenarios regarding exhaustible resource use, carbon emissions and technological change. Their results show that no or only little policy intervention should be necessary in order to limit the temperature rise. It is important to notice that their model assumes continuously decreasing production costs for solar energy by 30 to 50 percent per decade to reach this conclusion.

Next to the specifically policy related literature, a great focal point is the development of theoretical models to explain and predict economic growth and technological change. The neo-classical growth model, mainly developed by Solow [17] and Swan [20] in the 1950s, creates economic growth by increasing the capital to labour ratio. Due to diminishing returns to capital and labour however, this is only possible until a so called steady-state is reached. Thereafter, growth can only be achieved by technological change. This generation of economic growth models takes the technological change as exogenous, and thus does not actually explain long run growth. In the late 1980s and early 1990s, a new class of growth models evolved around the paper by Romer [15]. Technological change is here modelled as a product of economic activity, and thus endogenous. The emphasis is placed on Human capital and the development of technology. Knowledge, with increasing marginal productivity as opposed to the diminishing marginal returns of labour and capital, was now considered as a production factor. Realizing the incredible role knowledge, innovations and thus technological improvements play in economic growth, the nature of technical change developed to a field on its own. As Acemoglu however pinpointed only in 2002, also the large and influential literature on technical progress by Romer, Segerstrom,

> "does not address questions related to the direction and bias of technical change" (Acemoglu 2002, p. 1 [1]).

Combined with the aim of continued economic growth, the interesting question then raised was how technological change is actually distributed among the sectors of an economy or among different production factors, and how, as well as to which extent, this "natural" allocation given by existing knowledge stocks and historic events can be channelled towards a desired direction.

Acemoglu is a main contributor to directed technical change theory, he wrote an article with the same title in 2002 [1]. It states that technical change is either labour augmenting (as mostly during the last 60 years) or capital augmenting (as mostly during the previous century). Two opposing forces determine the direction of technological change: a market size effect and a price effect. The first one leads investment towards the production of factors with the larger market, the latter one towards production of more expensive goods (and thus higher revenues). Acemoglu concludes that an elasticity of substitution $\neq 1$ between the production factors leads to technical change directed towards the more abundant factor. If great enough, the substitution effect could even be overcome and result in a long run increase of the relative demand for this factor. Thus, in the case of gross substitutes, the market size effect dominates the price effect and there are incentives to improve the productivity of the abundant factor. In the case of gross complements, the price effect dominates.

In 2009, Acemoglu et al. released another paper [3] which developed the theoretical foundation into a new direction, namely applying it to the climate change debate and looking at clean and dirty production factors.

They show that under certain assumptions sustainable long run growth can be achieved with only short term policy interventions, at least in the case of strong substitutes. Delaying the necessary policy interventions is very costly. If the dirty input factors are exhaustible, the development of clean technologies occurs faster. They also expand the model to a two country setting representing the North and the South; in this scenario a change towards clean technology in the North might be enough to avoid an environmental disaster altogether. The market size and the price effect are again found, as well as the importance of the substitutability of production factors in order to achieve a sustainable development.

An adaptation of Acemoglu's model has been developed by Smulders and de Nooij in 2002 [16], in which they concentrate on aggregate growth in a framework with two production factors labour and energy and induced technical change. They allow, in contrast to Acemoglu, for a continuous increase in relative energy supply and assume a fixed elasticity of substitution between labour and energy of below one (gross complementarity). Their growth model is consistent with some important stylized facts, namely that over the last 60 years energy efficiency has improved, per capita energy use has increased, the share of energy cost of GDP has declined and energy prices on average have declined, too.

The work of Hart 2009 and 2010, "The natural resource see-saw" and "Directed technological change" both aim on enlightening further the interaction of long run factor shares and factor quantities, given endogenous directed technological change. The emphasis here lies on the effect of linked knowledge stocks, the elasticity of substitution between the production factors and the possibility of a stable balanced growth path.

The analysis now will focus on resource data in the light of directed technological change. To do so, the two production factors and resource sectors “labour” and “metals” shall be looked at, as well as two factors within the same sector, “aluminium” and “iron”. The model to which the data will be applied first of all needs to establish the substitutability of the factors in question since the focus of this work is to test the implications that result basically from Acemoglu’s, but mainly and more precisely from Hart’s work. Depending on the elasticity of substitution between production factors, the factor shares are expected to return to a stable balanced growth path or to keep rising after an initial increase in factor abundance of one production factor. Therefore a balanced growth path or a corner solution can be obtained, depending on the elasticity of substitution as well as the knowledge spillovers between them. A CES production function with two production factors will be transform into the reduced-form equation, which can then be used to econometrically estimate the elasticity of substitution between them. A short run as well as a long run elasticity should be found. The factor shares of the production factors are then looked at, in order to analyse their behaviour towards relative factor abundance.

The main results are that labour and metals, against any expectation, seem to be substitutes, and that aluminium and iron appear to be complements, whereas one should expected them to be rather substitutes. It is found that the theoretical framework which the aggregate resource data was applied to might not be appropriate. In the future it will be necessary to look at resource data within an economic sector or to enhance the model, by taking into account the change in sector sizes over time as well as the relative changes in factor quantities and prices on the aggregate level.

The first part of the analysis now contains a brief summary of the relevant theoretical models and assumptions on which this study is based.

Subsequently, a model which can be tested empirically will be developed and the utilized data will be described. The estimation results are then presented and discussed in the subsequent chapter, coming full circle with the questions presented in this introduction.

2 Theory of directed technological change

In this section an overview of the theoretical models which lead to the assumptions about factor share behaviour in the light of complements and substitutes is given. Every model is usually developed within a rather detailed framework, however it will be exclusively focused on the parts related to linked knowledge stocks, the elasticity of substitution and factor share behaviour of production factors. For the whole background and all underlying assumptions see the respective cited literature.

The way the creation of knowledge/ innovations are modelled within the different theoretical frameworks has a major influence on the model's consequences. In Acemoglu's baseline Lab-equipment model (Acemoglu 2009a, ch. 13 [2]) one final good is produced with the inputs labour L_t and the available number of machines N_t. The innovation possibilities frontier is modelled as

$$\dot{N}_t = \eta Z_t \tag{2.1}$$

where N_t is the number of different inputs/ machines, Z_t is the investment into *R&D* and $\eta > 0$. In this endogenous growth model research is investment in equipment and not in the employment of labour. The balanced growth path (BGP) long run growth rate of the economy is

$$g* = \frac{1}{\theta}(\eta\beta L - \rho) \tag{2.2}$$

with the assumptions $\eta\beta L > \rho$ and $(1 - \theta)\eta\beta L < \rho$ which ensures that long run growth is greater than zero and the utility of a household is finite. The growth rate depends on the number of workers L. This model does not assume knowledge in particular but the invention of new goods, which increases the total available variety which in turn increases the utility of the consumers. Growth is obtained by an always increasing investment $Z(t)$ which is yet impossible with finite resources.

This model can be expanded to feature knowledge spillovers that arise from existing ideas, and innovations are then modelled as

$$\dot{N}_t = \eta N_t L_{Rt} \tag{2.3}$$

where N_t is the existing knowledge or the existing innovations and L_R is the labour force within research. The BGP has a constant number of workers, a constant interest rate and the same growth rate of the economy as above.

Acemoglu then turns towards biased technological change, searching for an explanation of the increase in both the relative supply of skilled workers as well as the skill premium over the sixty years (Acemoglu 2009a, ch. 15 [2]). The model involves two types of machines, labour and for example a type of capital augmenting ones. Two intermediate goods are produced competitively with two different sets of machines and are either labour or capital intensive. New machines are created by the same specification as in the lab-equipment model,

$$\dot{N}_{Lt} = \eta_L Z_{Lt} \tag{2.4}$$

$$\dot{N}_{Ht} = \eta_H Z_{Ht} \tag{2.5}$$

with Z_L the investment into discovering new labour-augmenting machines (Z_H capital augmenting, respectively). A CES production function is assumed for the final good. The present discounted value of profits of discovering new machines decides about the investment and depends on instantaneous profits for one of the production factors and the market interest rate. With a normalized-to-1 price of the final good, the profit is maximized subject to the cost and machine demand. Intermediate goods prices and the elasticity of substitution are derived. On the BGP consumption grows at a constant rate and the relative factor price is constant. Combined all together, the relative profitability for the two technologies is found to be

$$\frac{V_H}{V_L} = \left(\frac{p_H}{p_L}\right)^{\frac{1}{\beta}} \left(\frac{H}{L}\right). \tag{2.6}$$

This is an important relationship since it implies the market size- as well as the price effect: $\frac{V_H}{V_L}$ is increasing in $\frac{p_H}{p_L}$ and thus the higher the price of the respective intermediate good, the higher the incentive to invent machines that complement this factor. Technologies that augment scarce factors are thus favoured, assuming that scarce factors have a higher price. $\frac{V_H}{V_L}$ is also increasing in $\frac{H}{L}$, which leads to the market size effect. The more one factor is used, the greater becomes the market for it and innovations for this factor are encouraged. Eliminating relative factor prices by substitution of marginal product conditions and the equations for the net present discounted values of innovations in both sectors, the following equation holds:

$$\frac{V_H}{V_L} = \gamma^{\frac{\epsilon}{\sigma}} \left(\frac{N_H}{N_L}\right)^{\frac{1}{\sigma}} \left(\frac{H}{L}\right)^{\frac{\sigma-1}{\sigma}}. \tag{2.7}$$

The elasticity of substitution σ between the two intermediate goods determines here whether the price effect will dominate the market size effect or not: for $\sigma > 1$, $\frac{V_H}{V_L}$ is increasing in $\frac{H}{L}$ and decreasing for $\sigma < 1$.

Acemoglu then proposes that there is always a so-called weak equilibrium bias, meaning that an increase in $\frac{H}{L}$ always leads to induced relatively H-biased technological change (for $\sigma > 1$ an increase in the BGP relative factor-augmenting technologies is relatively biased towards H and for $\sigma < 1$ there is a decrease in $\frac{N_H*}{N_L*}$ which is relatively biased towards H). There might also be a strong equilibrium bias if $\sigma > 2$, which means that an increase of $\frac{H}{L}$ raises the relative factor price $\frac{w_H}{w_L}$ whereby the curve of relative demand for technologies becomes upwards sloping.

> "The market size effect [...] can create sufficiently strong induced technological change to increase the relative marginal product and the relative price of the factor that has become more abundant." (Acemoglu 2009a, p. 511 [2]).

This can be seen in the BGP equation of the relative factor price ratio (2.8), which is a combination of the BGP ratio of relative technologies and the expression for relative wages:

$$w* \equiv \left(\frac{w_H}{w_L}\right)^* = \eta^{(\sigma-1)}\gamma^{\epsilon}\left(\frac{H}{L}\right)^{(\sigma-2)}. \tag{2.8}$$

In a next step knowledge spillovers will be introduced. The creation of new machines is here formulated for the two sectors as

$$\dot{N}_{Lt} = \eta_L N_{Lt}^{(1+\delta)/2} N_{Ht}^{(1-\delta)/2} S_{Lt} \tag{2.9}$$

and

$$\dot{N}_{Ht} = \eta_H N_{Lt}^{(1-\delta)/2} N_{Ht}^{(1+\delta)/2} S_{Ht} \tag{2.10}$$

with $\delta \leq 1$ and $S_{L/Ht}$ the number of scientists working to produce L- or H-augmenting machines. Acemoglu introduces the term state dependence for δ, whereby zero state dependence means that both sector's technologies create spillovers to the other sector, independent of the actual levels of N_L and N_H. A state dependence of one means that the levels of N_L and N_H are very important and an increase in the stock of machines in one sector will increase future innovations in this sector, but has no influence on the other sector's augmenting technology innovations.

In case of $\delta = 0$, all results about the direction of technological change will be the same as in the previous section. For $\delta > 0$, the BGP equation of the relative factor price ratio becomes

$$w* \equiv \left(\frac{w_H}{w_L}\right)^* = \eta^{\frac{(\sigma-1)}{(1-\delta\sigma}} \gamma^{\frac{(1-\delta]\epsilon}{1-\delta\sigma}} \left(\frac{H}{L}\right)^{\frac{(\sigma-2+\delta)}{1-\delta\sigma}} . \tag{2.11}$$

It is now easier to obtain strong equilibrium bias: if factor H becomes more abundant than the factor L, first of all an increase of relative innovations favouring factor H is encouraged, assuming $\sigma > 1$. If in addition there is state dependence, a rise in this relative technology makes further increases of this technology even more profitable. Thus, following from equation (2.11), there is strong equilibrium bias when $\sigma > 2 - \delta$ and an increase in relative factor abundance increases the relative marginal product as well as the relative wage of this factor. The condition for strong equilibrium bias then implies that an elasticity of less than 2 (how much less depends on δ) can suffice to generate the strong equilibrium bias. The value of state dependence δ itself is however rather difficult to measure in reality.

On the unique BGP there are constant relative technologies, and consumption and output grow at a constant rate. The transitional dynamics show however that the BGP is not always reached: Assuming $\sigma < \frac{1}{\delta}$, state dependence and initial levels of both technologies N_H and $N_L > 0$, then if the relative technology level is below the equilibrium level, $\frac{N_H}{N_L} < \left(\frac{N_H}{N_L}\right)^*$, investment Z in $N_H > 0$ and investment in $N_L = 0$ until the equilibrium relative technology level is reached. The opposite is true if the initial relative technology level is above the equilibrium. Thus there exists a unique equilibrium path.

If $\sigma > \frac{1}{\delta}$ however, starting with relative technology level above the equilibrium $\frac{N_H}{N_L} > \left(\frac{N_H}{N_L}\right)^*$, the economy will tend to continue rising $\frac{N_H}{N_L}$ towards ∞ as time goes towards ∞. An initial relative technology level below the equilibrium one $\frac{N_H}{N_L} < \left(\frac{N_H}{N_L}\right)^*$ will here lead to a relative technology level of 0 as time goes to ∞. There exists no equilibrium path.

Returning to the phenomenon of increasing relative supply of skilled labour and increasing wages, Acemoglu concludes that, assuming the two factors labour and capital whereby capital accumulates and state dependence is $\delta = 1$ and an elasticity of substitution between labour and capital of $\sigma < 1$, then

> “capital accumulation increases the price of labor more than proportionately, and the profits from labor-augmenting technologies increase more than the profits from capital-augmenting ones. This encourages further labor-augmenting technological change” (Acemoglu 2009a, p. 522 [2]).

A balanced allocation of effective units of capital and labour then leads to an equilibrium path where labour-augmenting technologies grow faster than capital-augmenting ones.

An earlier work directed towards induced innovation theory which is not as detailed as Acemoglu’s modelling described above, but which puts an emphasis on factor shares was published in 1964 by Kennedy [10]. He introduced the purely technological innovation possibilities frontier and stated that this is what determines innovations as well as the long run (constant) factor shares, and not the form of the production function.

An even stronger focus on factor shares connected to technological change is given by Hart's paper "Directed Technological Change" which will be presented at the conference SURED 2010 in Ascona [8]. Hart states that there is a need for a new type of directed technological change model which does not rely on a centralized economy and a perfect market, or the assumptions Acemoglu bases his model on. This is important in order to understand not only the skilled labour phenomenon but also the observation that a rapid rise in the fossil fuel production in the 20th century was usually followed by a rapid fall in price, with an approximately constant factor share. He sets up a general basic model that features knowledge spillovers, factor augmenting technological change and a potential balanced growth path for constant factor quantities. Many firms produce output y for which two production factors a and b are used, in different quantities by each firm. Factor augmenting technologies k_a and k_b are combined with the factor quantities to effective quantities. The knowledge functions for factor augmenting knowledge depend both on the existing knowledge (or quality) vectors in their own sector as well as in the other sector, and the investment in its own sector:

$$k_{a,t+1} = g(k_{at}, k_{bt}) \frac{I_{a,1+t}^{\phi}}{r_a} \tag{2.12}$$

$$k_{b,t+1} = g(k_{bt}, k_{at}) \frac{I_{b,1+t}^{\phi}}{r_b}. \tag{2.13}$$

In the scenario of independent knowledge stocks, factor a augmenting knowledge does not help to increase knowledge augmenting factor b. On a balanced growth path knowledge in all sectors grows at the same rate, factor quantities are constant and factor prices rise by the same rate as the knowledge stocks. If this is the case in period t, it will be as well in period $t+1$. Assuming symmetric firms and total depreciation of private knowledge from period to period in both sectors and CES production functions for each firm, the increase of relative knowledge and the relative investment can be combined and simplified to receive the equations which describe how the economy develops from a given level K:

$$G_t = \left[Q_{t+1}^{\eta} \left(\frac{r_b}{r_a} \right) F(K_t) K_t^{\eta} \right]^{\frac{1}{1-\eta}} \tag{2.14}$$

$$P_t Q_t = (K_t Q_t)^{\frac{\epsilon-1}{\epsilon}}. \tag{2.15}$$

G is here the increase of relative knowledge from period t to period $t+1$, Q the relative factor quantity, F reflects knowledge spillovers between the sectors, P is the relative factor price $\frac{a}{b}$, K the relative knowledge $\frac{k_a}{k_b}$, $\eta = \phi(\epsilon - 1)$ and ϵ the the elasticity of substitution between the two production factors. Q is given exogenously and K is the state variable. For F=1 (independent knowledge stocks), η is the elasticity of G with respect to K which is positive for $\epsilon > 1$ and negative for $\epsilon > 1$. Studying equation (2.14) then shows that when the factors are complements, an increase in the factor specific knowledge decreases the relative factor knowledge growth G. When the factors are substitutes thus the increase in K leads to an increase in G. Toward the corner solutions, when K approaches 0 or ∞, G will thus approach 0 or ∞ in the case of $\epsilon < 1$. Therefore, a rise in quantity a reduces investment in factor a augmenting knowledge, and the former increase is being reversed. For substitutes investment will increase when there is a rise in factor quantity and rise further the relative quantity. There is a unique, globally stable

BGP when the factors are complements, but it is unstable when they are substitutes.

Hart turns then to the case of constant elasticity knowledge dependence with the knowledge function

$$F(K_t) = K_t^{\sigma_c} \tag{2.16}$$

with $\sigma_c \in (0,]$ and σ_c measuring how closely both knowledge levels are connected to each other. The result of an analysis under this assumption is that with $\sigma_c > \eta$ there is a globally stable BGP. With $\sigma_c < \eta$ it is unstable and will approach a corner solution with only one of the factors earning all returns. This can be derived as before from the following equation incorporating the specific knowledge function:

$$G_t = \left[Q_{t+1}^{\eta} \left(\frac{r_b}{r_a} \right) K_t^{\eta - \sigma_c} \right]^{\frac{1}{1-\eta}}. \tag{2.17}$$

The stronger knowledge stocks are linked, the more a rise in relative knowledge levels drags the lower sector's level up and thus helps the stability.

Assuming now a level of knowledge linkage which relates to a stable BGP, Hart derives that an increase in the relative quantity of production factors leads to a decrease in the relative factor share to a new BGP for $\epsilon < 1$, and to an increase for $\epsilon > 1$. This is true since, under the assumption of a stable BGP to start with $\sigma_c > \eta$ (as derived above) and $G = 1$, from equation (2.17) one can derive that $\widetilde{K} = \left[\frac{r_b}{r_a} Q^{\eta} \right]^{\frac{1}{\sigma_c - \eta}}$ and thus

$$\widetilde{K}Q = \left(\frac{r_b}{r_a} \right)^{\frac{1}{\sigma_c - \eta}} Q^{\frac{\sigma_c}{\sigma_c - \eta}} \tag{2.18}$$

and therefore $\widetilde{K}Q$ will rise when Q rises.

Hart then adds a scenario where knowledge stocks are linked, but are not essential for the other sector. the knowledge function here is

$$F(K_t) = \frac{1}{K_t} \frac{K_t + \sigma_c}{1 + \sigma_c K_t} \tag{2.19}$$

with $\sigma_c \in (0, 1]$. A σ_c of 1 here means that an innovations in sector a is as useful in sector b, with $\sigma_c = 0$ knowledge of the respectively other sector is useless for the own knowledge. It is then shown that in the case that the two production factors are substitutes and the knowledge spillover is clearly below 1, there will not be a unique stable BGP (as for complements), but there will be two BGP: one where the first factor dominates, one where the other will dominate. The historically accumulated quantities will determine which factor would dominate if the relative quantity is raised. The important proven proposition then is that, with knowledge spillovers on a locally stable BGP, an increase in the relative quantity will increase the BGP factor share in the case of substitutes and decrease the factor share in the case of complements. It would be possible that, with knowledge spillovers and an elasticity of substitution greater than 1, a production factor would be abandoned from the production process altogether.

This drastic result leads to the question for complements and substitutes in the world's important production factors, on the one hand to explain historic developments deeper the factors labour and fossil fuels, but also a greater variety of factor uses. On the other hand, the knowledge about the substitutability of production factors will help to apply the correct policies when old technologies and factor usages shall be replaced by new ones, as it is the case with environmentally dubious and environmentally friendly ones: the theoretical framework let one assume that, in order to "automatically" phase out for example a dirty production process or production factor for environmental reasons, a substitute product and rather low knowledge transfer is theoretically needed to achieve this. The historically accumulated knowledge and available quantities also would play a major role in which type of long run growth path there will develop. So, an appropriate policy would therefore have to create a good-enough substitute for the dirty process, for example by subsidising the R&D in the cleaner, more desired sector or by putting a tax or a production limit on the dirty process. Increasing therefore the available knowledge and quantity of cleaner technology, the share of this sector could keep increasing and eventually take over completely. The closer the cleaner technology would be in availability and knowledge levels compared to the dirtier one, the shorter would the time period be during which an active policy is needed. When the substitute would have been established and reached a level above the dirtier one, it would carry on growing towards the here desired corner solution automatically.

3 The model

The aim of this work is to analyse the relationship between two production factors in the light of the above described theory. Therefore, the factor shares will be looked at and put in context with the elasticity of substitution between the factors.

To start with, a CES production function of one final good is considered, which is produced by two different inputs. The two production factors are X_1 and X_2 and w_1 and w_2 are their prices respectively. Knowledge stocks are in this very moment irrelevant since the exclusive interest here is the estimation of the elasticity of substitution between two production factors. Total costs then are minimized subject to the production function:

$$
\begin{aligned}
C(w_{1,2}, Q_t) &= \min_{X_{1t}, X_{2t}} \{ w_{1t} X_{1t} + w_{2t} X_{2t} \\
\textit{subject to } Q_t &= A \left[\delta X_{1t}^{-\rho} + (1-\delta) X_{2t}^{-\rho} \right]^{\frac{-1}{\rho}} \} \qquad (3.1)
\end{aligned}
$$

where $A > 0$, $0 < \delta < 1$ and $-1 < \rho \neq 0$. Putting up the Lagrangian one can derive the first order conditions

$$
\begin{aligned}
L &= w_{1t} X_{1t} + w_{2t} X_{2t} \\
&\quad + \lambda \left[Q - A \left[\delta X_{1t}^{-\rho} + (1-\delta) X_{2t}^{-\rho} \right]^{\frac{-1}{\rho}} \right] \\
\frac{\partial L}{\partial X_1} &= w_{1t} + \tfrac{1}{\rho} \lambda A \left[\delta X_1^{-\rho} + (1-\delta) X_{2t}^{-\rho} \right]^{\frac{-1}{\rho - 1}} \\
&\quad - \rho \delta X_{1t}^{-\rho - 1} \qquad = 0 \\
\frac{\partial L}{\partial X_2} &= w_{2t} + \tfrac{1}{\rho} \lambda A \left[\delta X_1^{-\rho} + (1-\delta) X_{2t}^{-\rho} \right]^{\frac{-1}{\rho - 1}} \\
&\quad - \rho (1-\delta) X_{2t}^{-\rho - 1} \qquad = 0
\end{aligned}
$$

and finally the reduced-form equation (3.2):

$$
\frac{X_{2t}}{X_{1t}} = \left(\frac{w_{1t}}{w_{2t}} \frac{1-\delta}{\delta} \right)^{\frac{1}{1+\rho}} \qquad (3.2)
$$

where $\frac{1}{1+\rho}$ equals σ (Arrow et al. 1961, p. 230). Expressing this relationship in logarithms yields

$$
\ln \left(\frac{X_2}{X_1} \right)_t = \sigma \ln \left(\frac{1-\delta}{\delta} \right) + \sigma \ln \left(\frac{w_1}{w_2} \right)_t \qquad (3.3)
$$

whereby σ here is the elasticity of substitution between the two production factors X_1 and X_2.

Equation (3.4) with $B = \sigma \log(\frac{1-\delta}{\delta})$ can now be estimated, using existent data for different natural resources.

$$\ln \left(\frac{X_2}{X_1} \right)_t = B + \sigma \ln \left(\frac{w_1}{w_2} \right)_t \tag{3.4}$$

Yet, thinking about the firm's decision making process of investment and production levels, the adjustment of the production process after a change in relative factor prices might not be accomplished within the same time period. It is much more reasonable to assume that the firm takes some average value of last periods' relative prices into account and makes then a decision about the production levels for the next period. The production process might thus not be alterable immediately. One can therefore replace the relative factor prices by its lag:

$$\ln \left(\frac{X_2}{X_1} \right)_t = B + \sigma \ln \left(\frac{w_1}{w_2} \right)_{(t-1)} \tag{3.5}$$

However, again assuming that full adaptation to more abundance of one factor is not reached within one period but takes time (since for example production technologies might be designed for a special type of input material and have to be replaced), a short term as well as a long term elasticity would be very interesting. The short run elasticity from one period to another would be expected to be very small, the long run elasticity however bigger The partial adjustment model as provided by Marc Nerlove [12] and described in Gujarati chapter 17 [7] can be used for this purpose. Starting with equation (3.4), it can be determined that $\frac{X_{2t}}{X_{1t}}$ is the desired, but not the known relative quantity for the given prices. This is due to adjustment processes within the firms and the economy. Thus,

$$\ln\left(\frac{X_2}{X_1}\right)_t^* = B + \sigma \ln\left(\frac{w_1}{w_2}\right)_{(t-1)} \tag{3.6}$$

The observed change in relative quantities from one period to the next would then be just a fraction (λ) of the optimal, desired change:

$$\ln\left(\frac{X_2}{X_1}\right)_t - \ln\left(\frac{X_2}{X_1}\right)_{(t-1)} = \lambda\left(\left(\frac{X_2}{X_1}\right)_t^* - \ln\left(\frac{X_2}{X_1}\right)_{(t-1)}\right) \tag{3.7}$$

with the adjustment coefficient $0 < \lambda \leq 1$. Solving this equation for $\ln\left(\frac{X_2}{X_1}\right)_t$ and substituting for $\ln\left(\frac{X_2}{X_1}^*\right)_t$ from equation (3.6):

$$\begin{aligned}
\ln\left(\frac{X_2}{X_1}\right)_t &= \lambda \ \ln\left(\frac{X_2}{X_1}\right)_t^* + (1-\lambda)\ln\left(\frac{X_{2t}}{X_{1t}}\right)_{(t-1)} \\
&= \lambda\left(B + \sigma \ln\left(\frac{w_{1t}}{w_{2t}}\right)_{(t-1)}\right) + (1-\lambda)\ln\left(\frac{X_{2t}}{X_{1t}}\right)_{(t-1)}
\end{aligned}$$

the estimable model (3.8) is received

$$\ln\left(\frac{X_2}{X_1}\right)_t = \lambda B + \lambda\sigma \ln\left(\frac{w_{1t}}{w_{2t}}\right)_{(t-1)} + (1-\lambda)\ln\left(\frac{X_{2t}}{X_{1t}}\right)_{(t-1)} \tag{3.8}$$

where $\sigma\lambda$ represents the short run elasticity, σ the long run elasticity and λ the coefficient of adjustment. In the case of gross substitutes, σ is expected to be ≥ 1 in absolute values, for gross complements as usually $\sigma < 1$.

4 Application 1: Metals and Labour

In this section the production factors labour and metals are analysed. The elasticity of substitution between them shall be estimated and the factor shares should be examined.

To start, an aggregate measure of all traded metals is created, utilizing data available from the U.S. Geological Survey [19]. The aggregated measure includes metal elements, metalloids and other metal containing commodities for which the amount of production and world prices are entirely reported between 1970 and 2006[1]. The metal price (in the following: w_1) has been aggregated by taking weighted averages relatively to the production proportions, the quantity (X_1) is just the sum of all production. Metals quantity is measured in metric tonnes and the price in 1998 US$. The metal quantity X_1 has increased by 130% between 1970 and 2006 and the metal price w_1 has decreased by just $17,6\%$ duing this period. The factor share of GGP[2] ($w_1 X_1 / GGP$) has also decreased over this time period. See figures 1aand 1b.

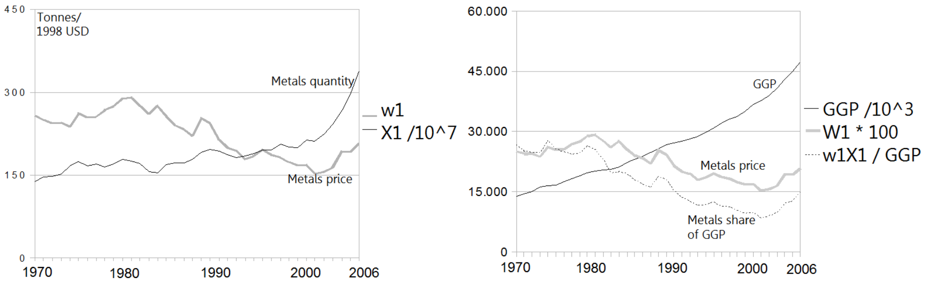
Internationally comparable labour cost or wage data is rather difficult to obtain. Freeman and Oostendorp compiled one ambitious data set for the NBER [6], called *Occupational wages around the world OWW*. The data base features 161 occupations in more than 150 countries from 1983 to 2003. All data reported has been adjusted to the US concept and therefore allows comparisons. However, the annual values are given for an ever changing number of reporting countries and a big variance in number of occupations

---

[1] Namely: aluminium, aluminium, antimony, arsenic, bauxite, beryllium, bismuth, cadmium, chromium, copper, germanium, hafnium, gold, iron and steel, iron ore, lead, lithium, magnesium compounds, magnesium metal, manganese, mercury, molybdenum, nickel, platinum-group metals, silver, strontium, tellurium, tin, titanium metal, tungsten, vanadium, zinc and zirconium mineral concentrates

[2] GGP here will be *Gross Global Product* which was extracted from the work of Angus Maddison "The world economy: historical statistics" [11] and shall represent a global measure corresponding to GDP. It is measured in 1990 International Geary-Khamis dollars (IGKD)

Figure 1: Aggregated Metals



(a) Production and Prices

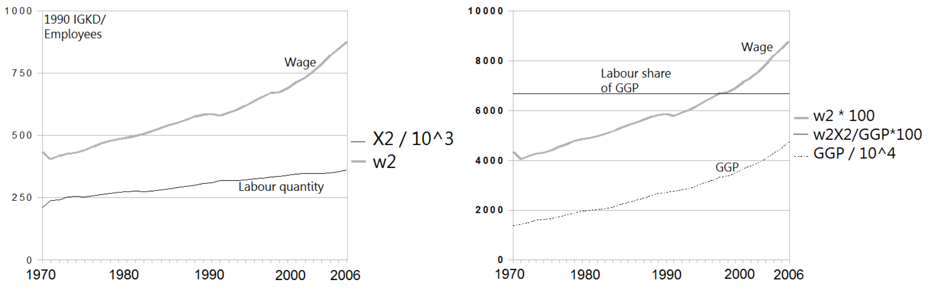
(b) Factor Share

covered. Since the reason for reporting and the type of reporting might be biased, this data set does not seem to offer a very reliable approximation of annual global labour costs.

Another possibility to approximate for a weighted average global wage would be to assume a fixed share of labour, which remains approximately constant at 2/3 of total GGP. One can therefore also define the price of labour as $w_2 = GDP/No.\ of\ employees \times 0,67$. The number of employees is taken from the International Comparisons of Annual Labor Force Statistics from the U.S. Bureau of Labor Statistics [13]. The data of employees is supplied for the ten countries USA, Canada, Australia, Japan, France, Germany, Italy, Netherlands, Sweden and the UK and was summed up in order to generate a proxy for the global number of employees. The number of employees shall be the labour quantity X_2.

The labour quantity X_2 has increased by 70% from 1970 to 2006 and the wage w_2 has approximately doubled. The labour share of GGP is constant at $0,67$ due to the definition. See figures 2a and 2b. The price of metals relative to labour has been continuously decreasing, the quantity of labour

Figure 2: Labour

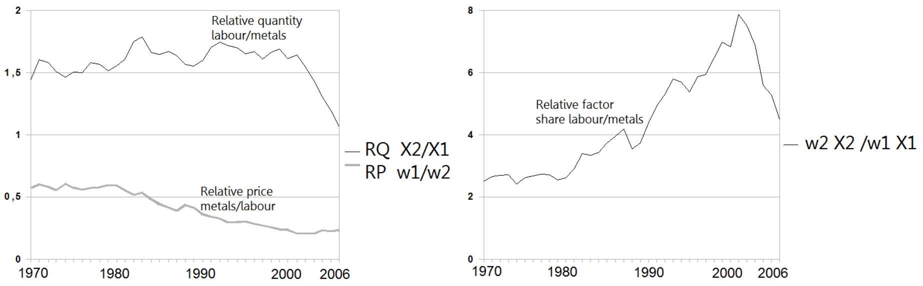


(a) Quantities and Wages

(b) Factor Share

relative to metals has slightly increased until around year 2000 and then been falling abruptly. The reason for looking at the relative price of metals over labour and the relative quantity labour over metals is that exactly these relative values are used within our estimable models. There is a strong rise of the relative factor share ($X_2 w_2 / X_1 w_1$): the relative-to-GGP factor share of labour has greatly increased relative to the falling factor share of metals. See figures 3a and 3b.

Figure 3: Metals and Labour



(a) Relative Quantities and Prices

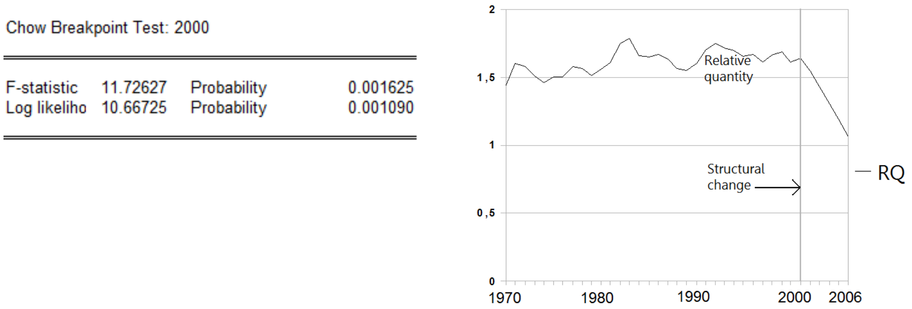
(b) Relative Factor Share

4.1 Tests of the hypotheses

The relative quantities of metals and labour seem to undergo a structural change at around year 2000. The Chow Breakpoint test confirms this assumption, since the null hypothesis of "no structural break" can be rejected on the 1% significance level, see figure 4a. For an analysis of both periods, before and after 2000, there are not enough observations in the second period. Therefore in the remaining section only a reduced sample of the observations from 1970 to 2000 will be used.

Figure 4: Structural Break of Relative Quantities

(a) Chow Breakpoint Test



```
Chow Breakpoint Test: 2000

F-statistic    11.72627   Probability     0.001625
Log likeliho   10.66725   Probability     0.001090
```

The variables $RQ_X = \left(\frac{X_2}{X_1}\right)$, the relative factor quantity, and $RP_w = \left(\frac{w_1}{w_2}\right)$, the relative factor price, are created. However, neither the series of the relative quantities nor the one of relative prices are stationary (see figures 9a and 9b, appendix). Both series are integrated by the order one and their first differences are indeed stationary, as shown in appendix figure 10. The classical approach here would be to use the differenced, stationary series for the regression analysis. However, due to the differencing all information about long term relationships would get lost. Since the variables however might be related also in the long run, one should first of all test for cointegration. If two non-stationary time series are cointegrated, a linear combination of the two series will be stationary. This combination is called the cointegration equation and expresses the long run equilibrium relation between them, see Franses chapter 10 [5]. The Johansen Cointegration Test however shows that RP_w and RQ_X are not cointegrated (appendix figure 11) and the data series should be differenced in order to obtain stationary variables. long run information will then however be lost.

The next step is to the estimation of the elasticity of substitution between metals and labour with the adapted equation (3.4):

$$\ln(RQ_X) = B + \sigma \ln(RP_w)_{(t-1)} \tag{4.1}$$

The regression output for regression (4.1) is shown in figures 12a and 12b, appendix. For the original variables (level) the coefficient of $\ln RP_{w(t-1)}$, σ, is -0,08. The estimated coefficient is statistically significant on the 1 % level. For the regression with stationary, differenced variables the elasticity of substitution is $\sigma = 0,54$, it is however not significant on even the 10 % level.

One can also estimate the Nerlove model from equation (3.8):

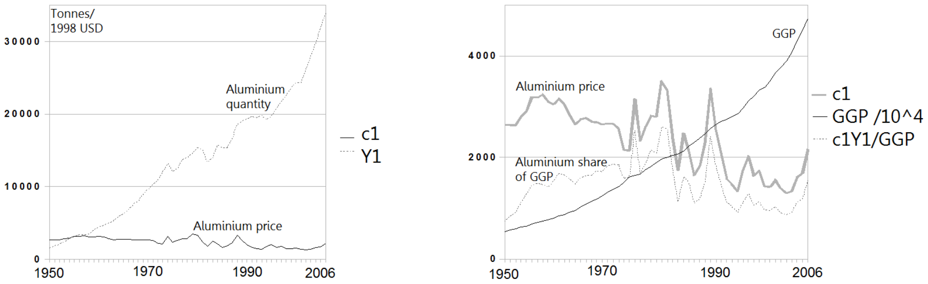
$$\ln(RQ_X) = B\lambda + \sigma\lambda \ln(RP_w)_{(t-1)} + (1-\lambda)\ln\left(RQ_{X(t-1)}\right) \tag{4.2}$$

As confirmed by EViews, there are not enough observations in the sample to estimate regression (4.2) with differenced, stationary variables. A simple regression however with non-differenced variables gives an adjustment coefficient of $\lambda = 1 - 0,59 = 0,41$ (see figure 13 appendix). The short run elasticity is -0,02, not significantly different from zero, and the long run elasticity σ is -0,04. The Wald Test reveals that the null hypothesis that $\frac{\lambda\omega}{(1-\lambda)} = 0$ can not be rejected; the long run elasticity is thus also not significantly different from zero.

5 Application 2: Production Factors Aluminium and Iron

For this analysis again the data set from the U.S. Geological Survey will be used, namely the production and price series of aluminium and iron. Figures 5a and 5b show the development of production quantities (in the following: Y_1) and prices (c_1) and the relative factor share of GGP (c_1Y_1/GGP). The time series from 1950 until 2006 will be used. The aluminium price c_1 has declined by $18,18\%$, the production Y_1 has increased by over 2000% over the total time span. Since the price has decreased only slightly, the immensely grown production and GGP lead to a factor share without any clear trend.

Figure 5: Aluminium



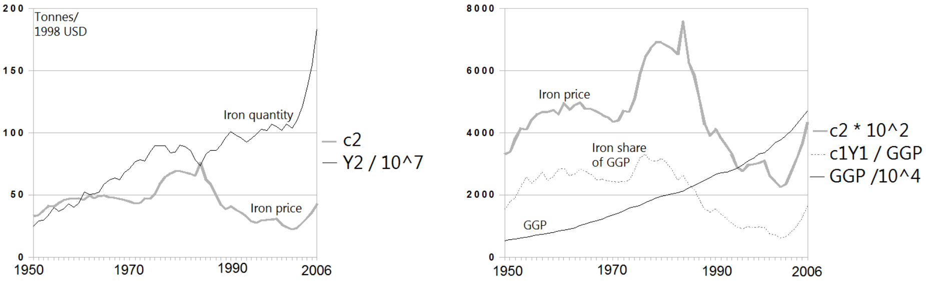
(a) Production and Prices

(b) Factor Share

From 1970 onwards, the price follows closely the factor share.

Figure 6a and 6b show the development of the price (c_2), quantity (Y_2) and factor share (c_2Y_2/GGP) of iron. The price experienced a rise until 1995 and returned than approximately to its initial level. Production has increased by more than 600%. The relative factor share thus also experienced a rise until around 1995 and then fell again, thus it returned approximately to its initial level.

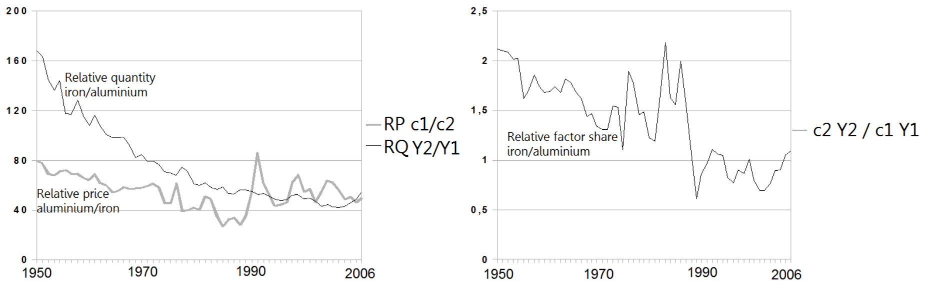
Figure 6: IRON



(a) Production and Prices **(b)** Factor Share

The development of relative prices is shown in figure 7a. Relative quantities have been decreasing, relative prices have been decreasing as well however with a high jump at around 1986. The relative factor share (c_2Y_2/c_1Y_1) can be seen in figure 7b. Since the factor share of iron has been rising until around 1986 but the share of aluminium fell until 1986, (c_2Y_2/c_1Y_1) is fluctuation around a rather stable average for this period. For the rest of the period the share of iron was rather stable, as was the share of aluminium. Therefore, the relative factor share was again quite constant, but on a lower level.

Figure 7: ALUMINIUM AND IRON

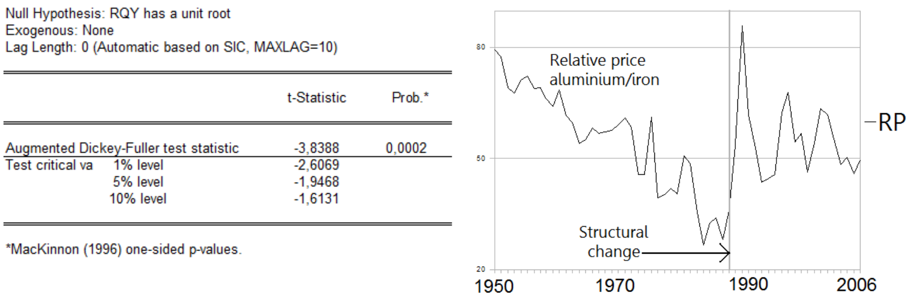

(a) Relative Quantities and Prices

(b) Relative Factor Share

5.1 Tests of the hypotheses

The series of relative prices, however, seems to have a structural break at 1986/1987. After fitting an AR(1) model to the RP_c series, it can be tested for a structural change with the Chow Breakpoint Test. The null hypothesis of no structural change from the periods before and after 1986 can be rejected on the 1% significance level. The analysis will thus be continued for two seperate time spans, period I (1950-1986) and period II (1987-2006). For

Figure 8: STATIONARITY, STRUCTURAL BREAK


(a) Relative Quantities: Unit Root Test

(b) Relative Prices: Structural Break

Null Hypothesis: RQY has a unit root
Exogenous: None
Lag Length: 0 (Automatic based on SIC, MAXLAG=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3,8388	0,0002
Test critical va	1% level	-2,6069	
	5% level	-1,9468	
	10% level	-1,6131	

*MacKinnon (1996) one-sided p-values.

period I, both variables are stationary (see appendix figure 15). For the sub-sample 1987-2006 however, RQ_y is not stationary but I(2) (appendix figure 16).

Two variables are created: $RQ_Y = \left(\frac{Y_2}{Y_1}\right)$, the relative factor quantity, and $RP_c = \left(\frac{c_1}{c_2}\right)$, the relative factor price, in order to estimate the elasticity of substitution between aluminium and iron. The equation adapted from (3.4) is

$$\ln RQ_{Yt} = B + \sigma \ln RP_{c(t-1)} \tag{5.1}$$

Period I:

σ is 0,99 with a p-value of 0,000 and thus very close to 1.

Period II:

σ is 0,46 (using the twice differenced RQ series), the coefficient is however not significant at all (p-value 0,67). See output in the appendix, figures 17 and 18.

The next step is to estimate equation (5.2) for both periods.

$$\ln RQ_{Yt} = B\lambda + \sigma\lambda \ln RP_{c(t-1)} + (1-\lambda) \ln RQ_{y(t-1)} \tag{5.2}$$

Period I:

The short run elasticity $\sigma\lambda$ is 0,096, regarding the p-value of 0,21 however it is not very significantly different from zero. The adjustment coefficient λ is 0,12 and thus the long run elasticity σ is 0,78. A Wald-Test for the hypothesis $\frac{\sigma\lambda}{1-\lambda} = 0$ gives a p-value of 0,025 (F-statistic) and the hypothesis that the long run elasticity is zero can thus be rejected on the 5% significance level.

Period II:

The short run elasticity $\sigma\lambda$ is -0,049, with a very high p-value of 0,4. The adjustment coefficient λ is -0,25 and the long run elasticity σ is 0,196. The coefficient test for the long run elasticity suggests not to reject the hypothesis that $\left(\frac{\sigma\lambda}{1-\lambda}\right) = 0$ since the p-value is 0,47 (F-statistic). See appendix figures 19a and 19b for the output tables.

6 Discussion

The preceding work started with a summary of the directed technological change theory which has been developed during the last eighty years. It was found that the introduction of (linked) knowledge stocks adds new aspects to the discussion of economic growth, as for example the question of a possible stable balanced growth path. Allowing for knowledge linkages, innovations in one sector can imply a knowledge increase for other sectors and therefore "drag" sectors with a lower knowledge level up. When knowledge is not linked, an innovation in both sectors is needed to keep the two active. The second point that adds further insight into economic growth theory was the substitutability between production factors, which might lead to a balanced growth path, or a corner solution in which only one production factor will be used in the long run.

Sections 4 and 5 shed quite some light on the behaviour of metals and labour and aluminium and iron as production factors. However, there are insufficiencies in the models applied here: neither the simpler model 1 from equation (3.4) nor the Nerlove model from equation (3.8), model 2, seem to solely lead to meaningful and significant results.

What appears reasonable is the assumption that model 1 should be useful in the event of a clear trend in the series. This should be true since the OLS regression simply keeps comparing just two points at the time, relative price at period t and relative quantity at $t + 1$. If there is a high volatility and no obvious trend in the data, the relative quantity might still be in the adjustment process when the next change in relative price takes place. Therefore it seems not very probable to catch such trends with model 1. A positive example for this model is the estimation for period I for aluminium and iron: both the relative quantities and the relative prices are clearly falling, even with a relatively stable slope. Model 1 here estimated a highly significant elasticity of substitution of 0,99, which relates to fixed proportions and a constant factor share. As was shown in figure 7b, the factor share is as a matter of fact about constant during this period.

However, the Nerlove model which is laid out to cover a short run as well as a long run effect, should be able to better handle a situation of high volatility. Looking at the estimation results though, only the short run elasticities seem reasonable, with an elasticity of substitution very close to zero. The long run elasticities are altogether insignificant (except of period I aluminium and iron with $\sigma = 0,8$ and thus close to 1 as also model 1 suggested). There are mainly two reasons for this result: firstly, there were not enough observations to run an estimation with both differenced and lagged variables, especially in the two periods case for aluminium and iron. Secondly, the assumed decision making process of a firm about the investment/ production levels in each period was not detailed enough. There are many possibilities how the relative quantities in period t might be decided. They could depend on last periods prices and quantities, this periods price, the expected prices for the upcoming 5 years, the price and quantity trend over the past couple of years, ...

The number of theoretically possible functions is huge and the most appropriate form could not be properly derived within the frame of this work. However, the Nerlove model in the form used above seems to be lacking important explanatory variables in order to give significant long run results.

The long term relationship between the prices and quantities of resources within the frame of directed technological change theory on an aggregated level are now however better understood. It could be seen that an increase in quantity of labour and prices can go hand in hand with an increase in quantity and a decreasing price for metals, with an increasing relative factor share. Thus, even though the relative quantity and the relative price stayed approximately constant, looking at the relative quantities and the relative factor share, labour and metals seem to be rather substitutes than complements for the available data. A small increase in relative labour quantity lead to a long run increase of its relative factor share. This is very surprising, since labour and metals are expected to be used complementary. One possible explanation for this result is that aggregated, world level data was used. For example, it is mathematically easily possible that the share of labour relative to metals falls within the different economic sectors over time, but that the share of labour relative to metals altogether on an aggregate level still increases.

The relative production of aluminium and iron increased greatly. Both the share of aluminium as well as the share of iron of the GGP however stayed relatively constant, and therefore the long run relative factor share of both dos not have a trend but is constant. According to the theory and this analysis, aluminium and iron had during this period an elasticity of substitution close to 1 which again suggests constant factor shares. This result is again very surprising. Instead of aluminium and iron being substitutes, the analysis suggests them to be complements. One might again be looking at a result which does represent the aggregate data, but not what is happening within the different sectors: the packaging industry for example could use either iron or aluminium in a substitutionary manner. In the transport sector, aeroplanes, cars and boats are not necessarily possible to substitute for each other and since they use iron and aluminium in different proportions for each vehicle, they most probably will behave like complements. Thus, the aggregate data shows just the aggregate result.

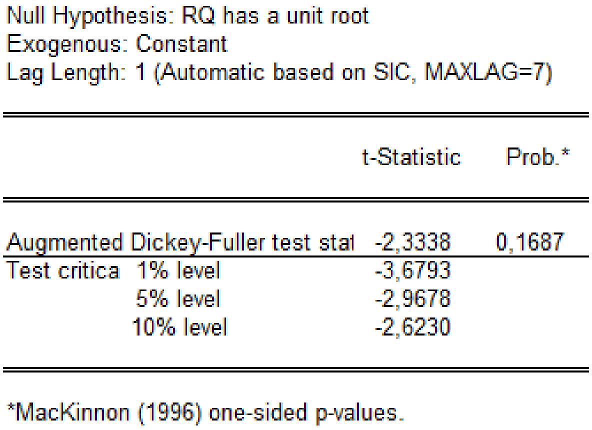
In the theoretical part it was found that, with little or no knowledge spillovers, complements will experience a balanced growth path and a constant factor share. This seems to fit the above empirical situation here quite well: the knowledge spillovers from labour to other types of factor augmenting knowledge like metals is expected to be much stronger than the expected knowledge spillovers from aluminium to iron, when labour is pictured as 2/3 of GGP. Aluminium and iron therefore exhibit here less knowledge spillovers between each other than labour augmenting knowledge might offer, and thus the constant factor share and the elasticity of substitution close to 1.

A simple follow-up research would involve to perform the above analysis on data within some specific sectors, a global perspective requires adjustments of the models. Acemoglu's model from 2002 [1] does already to some extend cover the intersectoral aspect, since it features in the beginning two production factors which are produced in different "sectors" which form the whole economy. However, it is important to emphasize the need for further research in this direction, to test the hypotheses regarding factor shares, relative factor quantities, substitutes and complements on an aggregate, global level. The change of relative sector sizes needs to be taken in into account, in order to give clear policy recommendations to encourage the use of environmental goods.

7 Appendix 1: Output Tables

Figure 9: UNIT ROOT TESTS

(a) Relative Quantities

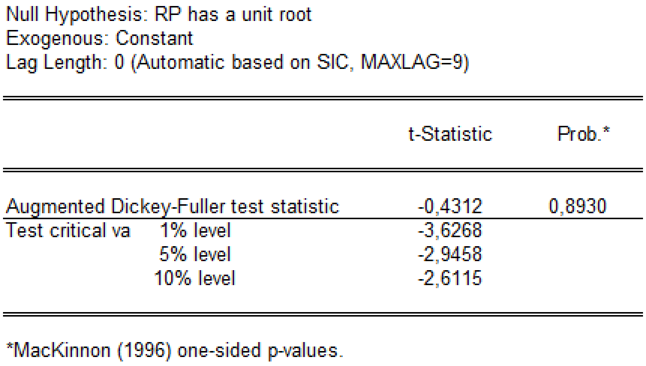


Null Hypothesis: RQ has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic based on SIC, MAXLAG=7)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test stat		-2,3338	0,1687
Test critica	1% level	-3,6793	
	5% level	-2,9678	
	10% level	-2,6230	

*MacKinnon (1996) one-sided p-values.

(b) Relative Prices



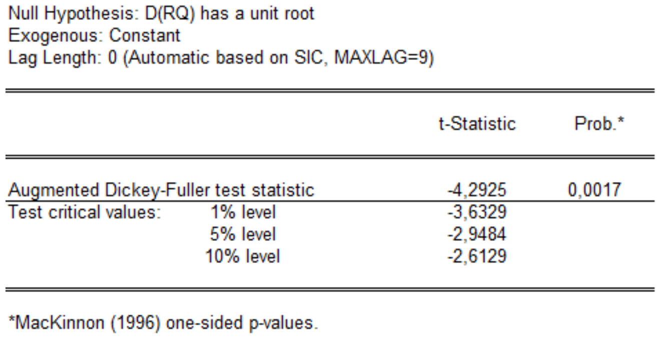
Null Hypothesis: RP has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic based on SIC, MAXLAG=9)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-0,4312	0,8930
Test critical va	1% level	-3,6268	
	5% level	-2,9458	
	10% level	-2,6115	

*MacKinnon (1996) one-sided p-values.

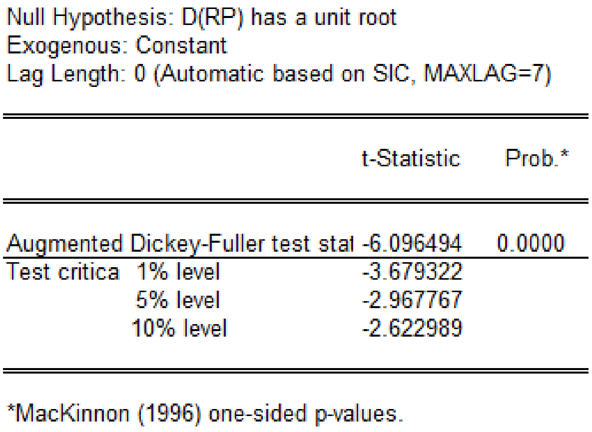
Figure 10: First Differences of RQ_X and RP_w

(a) d(RQ)



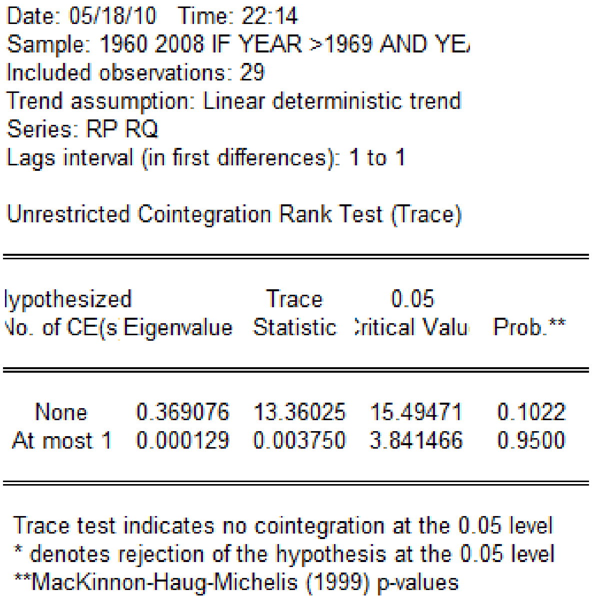
```
Null Hypothesis: D(RQ) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic based on SIC, MAXLAG=9)

                                                   t-Statistic     Prob.*

Augmented Dickey-Fuller test statistic               -4,2925       0,0017
Test critical values:          1% level              -3,6329
                               5% level              -2,9484
                              10% level              -2,6129

*MacKinnon (1996) one-sided p-values.
```

(b) d(RP)



```
Null Hypothesis: D(RP) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic based on SIC, MAXLAG=7)

                                  t-Statistic    Prob.*

Augmented Dickey-Fuller test stat -6.096494     0.0000
Test critica  1% level            -3.679322
              5% level            -2.967767
             10% level            -2.622989

*MacKinnon (1996) one-sided p-values.
```

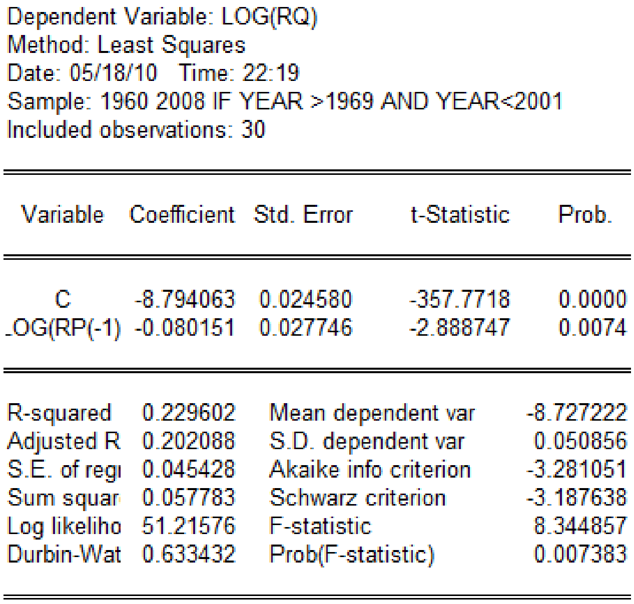
Figure 11: Johansen Cointegration Test



```
Date: 05/18/10   Time: 22:14
Sample: 1960 2008 IF YEAR >1969 AND YE
Included observations: 29
Trend assumption: Linear deterministic trend
Series: RP RQ
Lags interval (in first differences): 1 to 1

Unrestricted Cointegration Rank Test (Trace)

==========================================================
lypothesized                 Trace       0.05
lo. of CE(s Eigenvalue   Statistic  ritical Valu    Prob.**
==========================================================
   None      0.369076    13.36025   15.49471     0.1022
 At most 1   0.000129    0.003750   3.841466     0.9500
==========================================================

 Trace test indicates no cointegration at the 0.05 level
 * denotes rejection of the hypothesis at the 0.05 level
 **MacKinnon-Haug-Michelis (1999) p-values
```

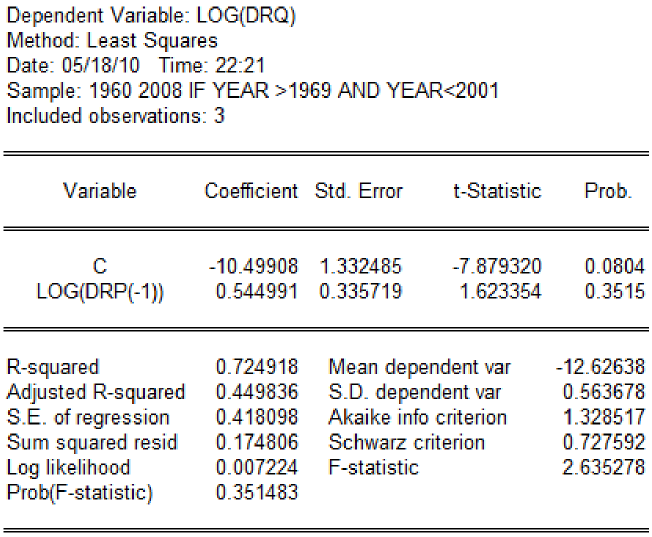
Figure 12: Estimation of Elasticity of Substitution

(a) Level



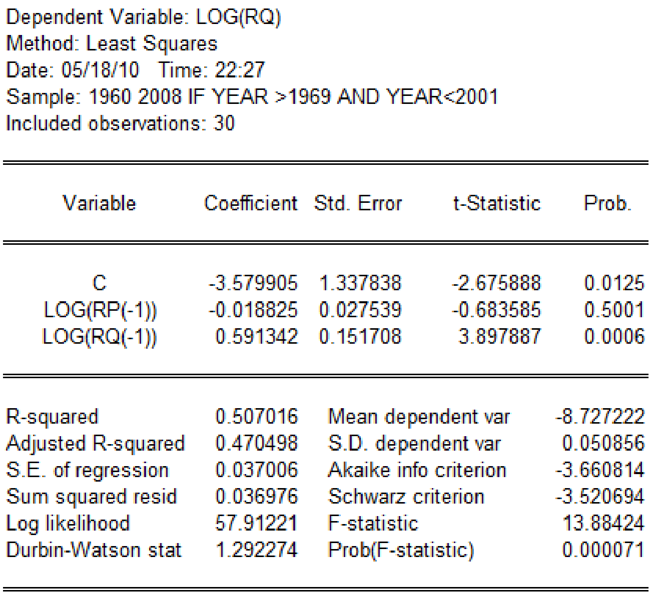
```
Dependent Variable: LOG(RQ)
Method: Least Squares
Date: 05/18/10   Time: 22:19
Sample: 1960 2008 IF YEAR >1969 AND YEAR<2001
Included observations: 30
==============================================================
 Variable    Coefficient  Std. Error     t-Statistic    Prob.
==============================================================
    C          -8.794063   0.024580      -357.7718     0.0000
_OG(RP(-1)  -0.080151   0.027746      -2.888747     0.0074
==============================================================
R-squared     0.229602   Mean dependent var       -8.727222
Adjusted R    0.202088   S.D. dependent var        0.050856
S.E. of regı  0.045428   Akaike info criterion    -3.281051
Sum squar     0.057783   Schwarz criterion        -3.187638
Log likeliho  51.21576   F-statistic               8.344857
Durbin-Wat    0.633432   Prob(F-statistic)         0.007383
==============================================================
```

(b) First Differences



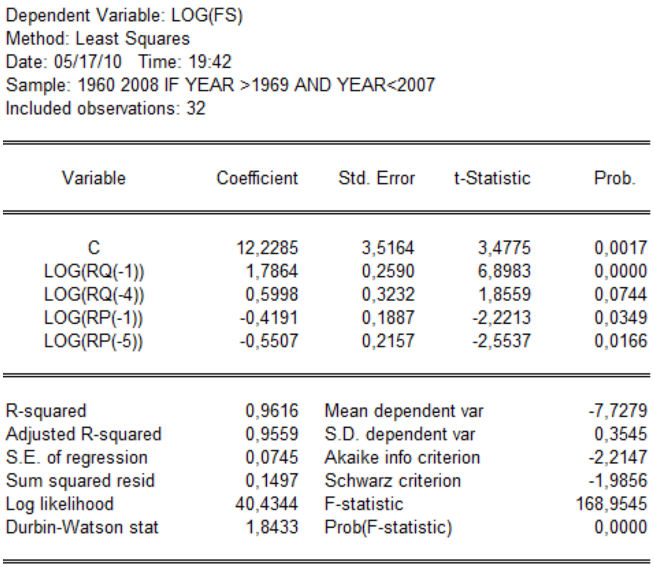
```
Dependent Variable: LOG(DRQ)
Method: Least Squares
Date: 05/18/10   Time: 22:21
Sample: 1960 2008 IF YEAR >1969 AND YEAR<2001
Included observations: 3
=====================================================================
        Variable        Coefficient  Std. Error    t-Statistic   Prob.
=====================================================================
            C             -10.49908   1.332485      -7.879320    0.0804
      LOG(DRP(-1))         0.544991   0.335719       1.623354    0.3515
=====================================================================
R-squared             0.724918   Mean dependent var      -12.62638
Adjusted R-squared    0.449836   S.D. dependent var        0.563678
S.E. of regression    0.418098   Akaike info criterion     1.328517
Sum squared resid     0.174806   Schwarz criterion         0.727592
Log likelihood        0.007224   F-statistic               2.635278
Prob(F-statistic)     0.351483
=====================================================================
```

Figure 13: Estimation of Partial Adjustment Model



```
Dependent Variable: LOG(RQ)
Method: Least Squares
Date: 05/18/10   Time: 22:27
Sample: 1960 2008 IF YEAR >1969 AND YEAR<2001
Included observations: 30

        Variable        Coefficient  Std. Error    t-Statistic    Prob.

           C            -3.579905    1.337838      -2.675888      0.0125
        LOG(RP(-1))     -0.018825    0.027539      -0.683585      0.5001
        LOG(RQ(-1))      0.591342    0.151708       3.897887      0.0006

R-squared                0.507016    Mean dependent var      -8.727222
Adjusted R-squared       0.470498    S.D. dependent var       0.050856
S.E. of regression       0.037006    Akaike info criterion   -3.660814
Sum squared resid        0.036976    Schwarz criterion       -3.520694
Log likelihood           57.91221    F-statistic              13.88424
Durbin-Watson stat       1.292274    Prob(F-statistic)        0.000071
```

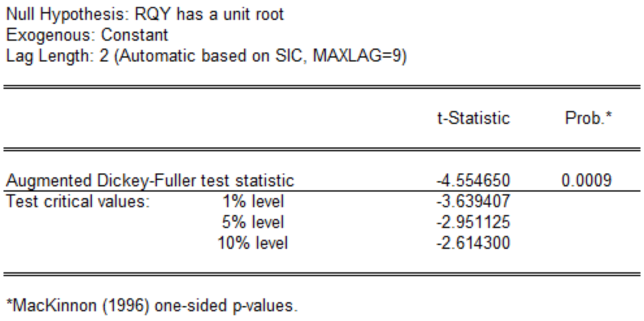
Figure 14: Factor share behaviour



```
Dependent Variable: LOG(FS)
Method: Least Squares
Date: 05/17/10   Time: 19:42
Sample: 1960 2008 IF YEAR >1969 AND YEAR<2007
Included observations: 32

        Variable          Coefficient     Std. Error    t-Statistic       Prob.

           C                12,2285         3,5164        3,4775          0,0017
        LOG(RQ(-1))          1,7864         0,2590        6,8983          0,0000
        LOG(RQ(-4))          0,5998         0,3232        1,8559          0,0744
        LOG(RP(-1))         -0,4191         0,1887       -2,2213          0,0349
        LOG(RP(-5))         -0,5507         0,2157       -2,5537          0,0166

R-squared                    0,9616     Mean dependent var            -7,7279
Adjusted R-squared           0,9559     S.D. dependent var             0,3545
S.E. of regression           0,0745     Akaike info criterion         -2,2147
Sum squared resid            0,1497     Schwarz criterion             -1,9856
Log likelihood              40,4344     F-statistic                  168,9545
Durbin-Watson stat           1,8433     Prob(F-statistic)              0,0000
```

Figure 15: Period I: Stationarity of RQ and RP, Aluminium and Iron

(a) Relative Quantities

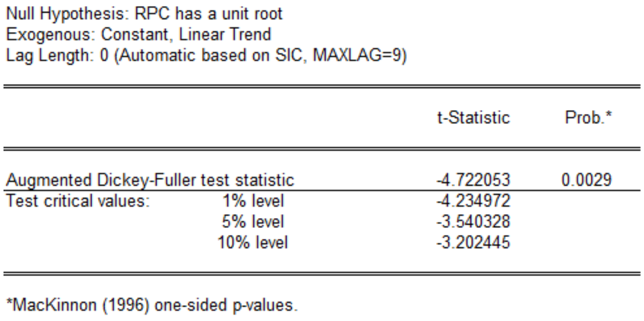


Null Hypothesis: RQY has a unit root
Exogenous: Constant
Lag Length: 2 (Automatic based on SIC, MAXLAG=9)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.554650	0.0009
Test critical values:	1% level	-3.639407	
	5% level	-2.951125	
	10% level	-2.614300	

*MacKinnon (1996) one-sided p-values.

(b) Relative Prices



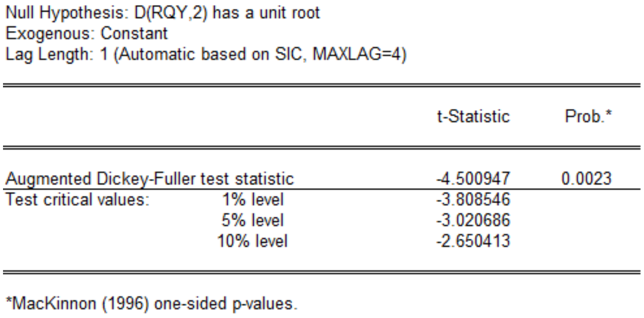
Null Hypothesis: RPC has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic based on SIC, MAXLAG=9)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.722053	0.0029
Test critical values:	1% level	-4.234972	
	5% level	-3.540328	
	10% level	-3.202445	

*MacKinnon (1996) one-sided p-values.

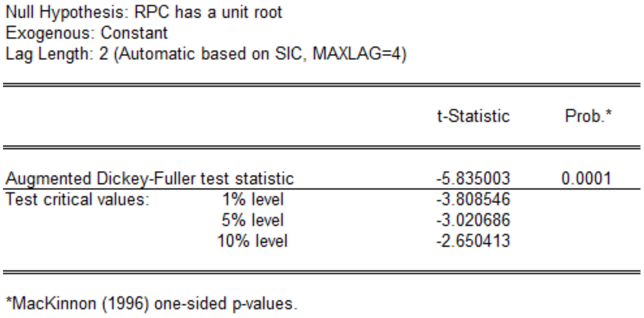
Figure 16: Period II: Stationarity of RQ and RP, Aluminium and Iron

(a) Relative Quantities



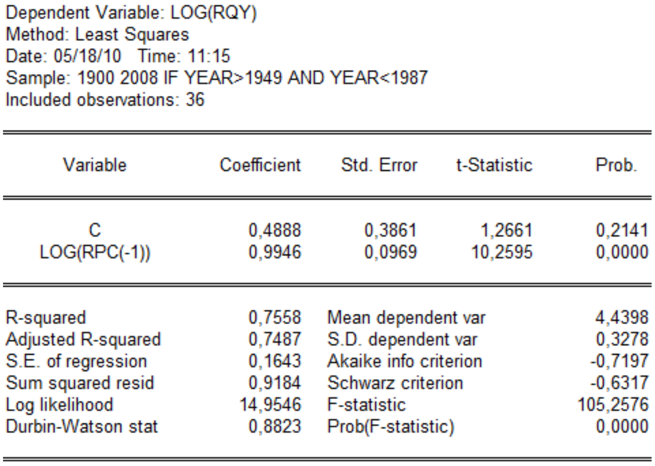
```
Null Hypothesis: D(RQY,2) has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic based on SIC, MAXLAG=4)

                                                  t-Statistic     Prob.*

Augmented Dickey-Fuller test statistic             -4.500947      0.0023
Test critical values:          1% level            -3.808546
                               5% level            -3.020686
                               10% level           -2.650413

*MacKinnon (1996) one-sided p-values.
```

(b) Relative Prices



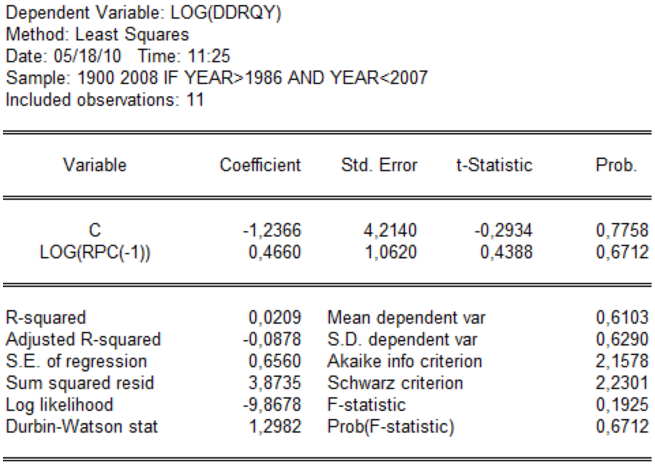
```
Null Hypothesis: RPC has a unit root
Exogenous: Constant
Lag Length: 2 (Automatic based on SIC, MAXLAG=4)

                                                  t-Statistic     Prob.*

Augmented Dickey-Fuller test statistic             -5.835003      0.0001
Test critical values:          1% level            -3.808546
                               5% level            -3.020686
                               10% level           -2.650413

*MacKinnon (1996) one-sided p-values.
```

Figure 17: Elasticity of Substitution: Period I



```
Dependent Variable: LOG(RQY)
Method: Least Squares
Date: 05/18/10   Time: 11:15
Sample: 1900 2008 IF YEAR>1949 AND YEAR<1987
Included observations: 36

        Variable          Coefficient    Std. Error    t-Statistic     Prob.

           C                 0,4888        0,3861        1,2661       0,2141
       LOG(RPC(-1))          0,9946        0,0969       10,2595       0,0000

R-squared                    0,7558   Mean dependent var               4,4398
Adjusted R-squared           0,7487   S.D. dependent var               0,3278
S.E. of regression           0,1643   Akaike info criterion           -0,7197
Sum squared resid            0,9184   Schwarz criterion               -0,6317
Log likelihood              14,9546   F-statistic                    105,2576
Durbin-Watson stat           0,8823   Prob(F-statistic)                0,0000
```

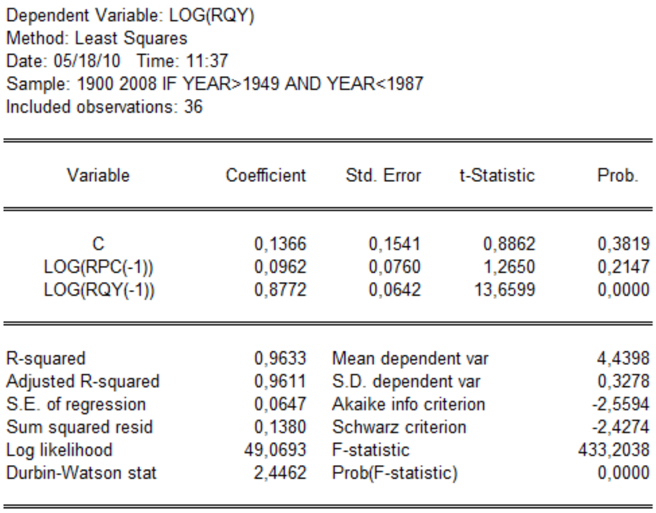
Figure 18: Elasticity of Substitution: Period II



```
Dependent Variable: LOG(DDRQY)
Method: Least Squares
Date: 05/18/10   Time: 11:25
Sample: 1900 2008 IF YEAR>1986 AND YEAR<2007
Included observations: 11

        Variable          Coefficient    Std. Error    t-Statistic     Prob.

           C                -1,2366        4,2140       -0,2934       0,7758
       LOG(RPC(-1))          0,4660        1,0620        0,4388       0,6712

R-squared                    0,0209   Mean dependent var               0,6103
Adjusted R-squared          -0,0878   S.D. dependent var               0,6290
S.E. of regression           0,6560   Akaike info criterion            2,1578
Sum squared resid            3,8735   Schwarz criterion                2,2301
Log likelihood              -9,8678   F-statistic                      0,1925
Durbin-Watson stat           1,2982   Prob(F-statistic)                0,6712
```

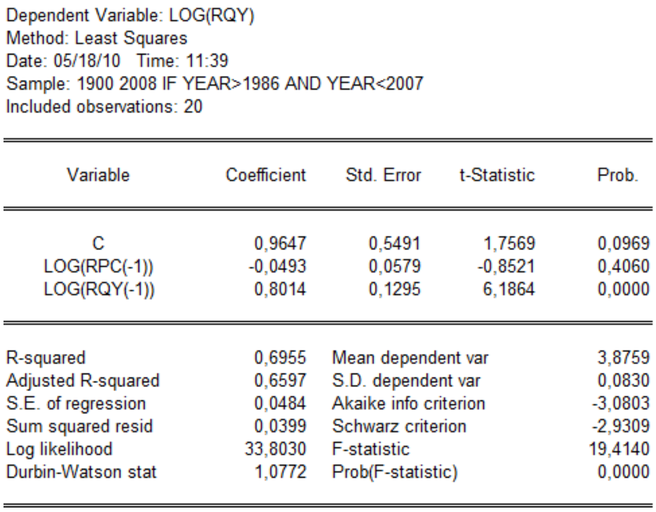
Figure 19: Estimation of Partial Adjustment Model

(a) Period I



```
Dependent Variable: LOG(RQY)
Method: Least Squares
Date: 05/18/10   Time: 11:37
Sample: 1900 2008 IF YEAR>1949 AND YEAR<1987
Included observations: 36

        Variable        Coefficient   Std. Error   t-Statistic     Prob.

            C              0,1366       0,1541       0,8862       0,3819
       LOG(RPC(-1))        0,0962       0,0760       1,2650       0,2147
       LOG(RQY(-1))        0,8772       0,0642      13,6599       0,0000

R-squared                  0,9633   Mean dependent var          4,4398
Adjusted R-squared         0,9611   S.D. dependent var          0,3278
S.E. of regression         0,0647   Akaike info criterion      -2,5594
Sum squared resid          0,1380   Schwarz criterion          -2,4274
Log likelihood            49,0693   F-statistic               433,2038
Durbin-Watson stat         2,4462   Prob(F-statistic)           0,0000
```

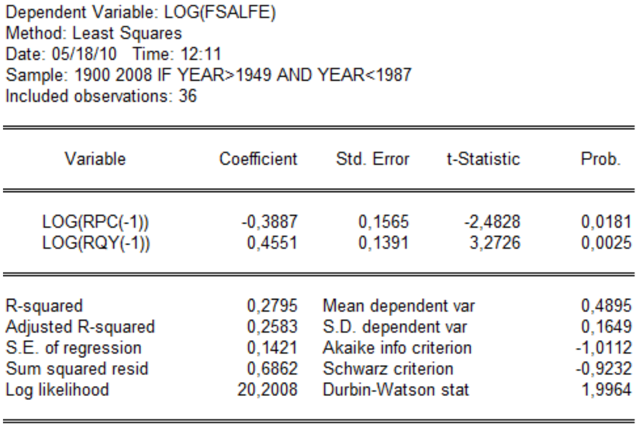
(b) Period II



```
Dependent Variable: LOG(RQY)
Method: Least Squares
Date: 05/18/10   Time: 11:39
Sample: 1900 2008 IF YEAR>1986 AND YEAR<2007
Included observations: 20

        Variable        Coefficient   Std. Error   t-Statistic     Prob.

            C              0,9647       0,5491       1,7569       0,0969
       LOG(RPC(-1))       -0,0493       0,0579      -0,8521       0,4060
       LOG(RQY(-1))        0,8014       0,1295       6,1864       0,0000

R-squared                  0,6955   Mean dependent var          3,8759
Adjusted R-squared         0,6597   S.D. dependent var          0,0830
S.E. of regression         0,0484   Akaike info criterion      -3,0803
Sum squared resid          0,0399   Schwarz criterion          -2,9309
Log likelihood            33,8030   F-statistic                19,4140
Durbin-Watson stat         1,0772   Prob(F-statistic)           0,0000
```

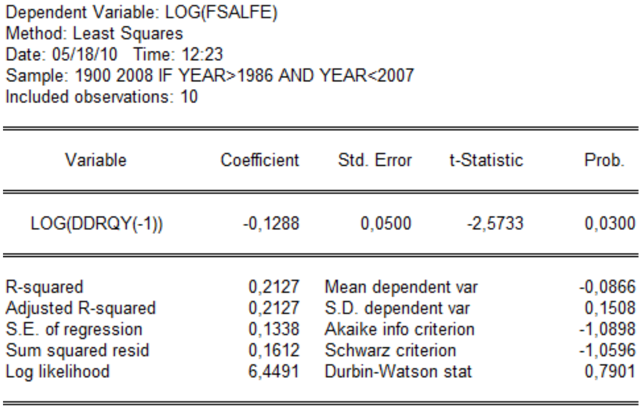
Figure 20: Factor Share Behaviour, Aluminium and Iron

(a) Period I



```
Dependent Variable: LOG(FSALFE)
Method: Least Squares
Date: 05/18/10   Time: 12:11
Sample: 1900 2008 IF YEAR>1949 AND YEAR<1987
Included observations: 36

        Variable          Coefficient    Std. Error    t-Statistic      Prob.

     LOG(RPC(-1))           -0,3887        0,1565        -2,4828        0,0181
     LOG(RQY(-1))            0,4551        0,1391         3,2726        0,0025

R-squared                    0,2795    Mean dependent var               0,4895
Adjusted R-squared           0,2583    S.D. dependent var               0,1649
S.E. of regression           0,1421    Akaike info criterion           -1,0112
Sum squared resid            0,6862    Schwarz criterion               -0,9232
Log likelihood              20,2008    Durbin-Watson stat               1,9964
```

(b) Period II



```
Dependent Variable: LOG(FSALFE)
Method: Least Squares
Date: 05/18/10   Time: 12:23
Sample: 1900 2008 IF YEAR>1986 AND YEAR<2007
Included observations: 10

        Variable          Coefficient    Std. Error    t-Statistic      Prob.

   LOG(DDRQY(-1))           -0,1288        0,0500        -2,5733        0,0300

R-squared                    0,2127    Mean dependent var              -0,0866
Adjusted R-squared           0,2127    S.D. dependent var               0,1508
S.E. of regression           0,1338    Akaike info criterion           -1,0898
Sum squared resid            0,1612    Schwarz criterion               -1,0596
Log likelihood               6,4491    Durbin-Watson stat               0,7901
```

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