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Investment in High-tech Industries: An Example from the LCD Industry*

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Abstract

This paper considers a representative firm taking investment decisions in a high-tech environment where different generations of products are invented over time. First, we develop a real options investment model in which, according to standard practice, the sales price and the unit production cost both satisfy a geometric Brownian motion (GBM) process. However, from real life data of the LCD industry it follows that output prices behave according to a crystal cycle that does not match a GBM. We proceed by conducting a thorough econometric analysis, leading to the conclusion that a vector autoregressive model (VAR) provides the best fit. Integrating this model with the real options machinery, we find that (i) at the moment of investment the increased production capacity goes along with increasing production cost and decreasing price, (ii) a management effect is present in the sense that a price drop is followed by a cost decrease due to management pushing harder on cost decreasing programs, and (iii) investing can be optimal while at the same time a GBM yields a negative net present value (NPV). We also find that investment decisions taken in practice are better supported by our VAR model than by the standard real options model based on GBM.

Keywords: High-tech Investment, Investment under Uncertainty, Product Innovation, Real Options, Vector Autoregressive Model
JEL classification: C32; D92; E22; O33

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1 Introduction

Due to the very advanced technology involved, investments in high-tech industries usually require significant irreversible investments. In a special report on Samsung Electronics in The Economist (January 15th, 2005, p. 60) it is stated that

"Capital spending is more than \$5 billion. The company is building the world's most advanced factory for making giant liquid crystal displays (LCDs), and between now and 2010 intends to spend around \$24 billion on new chipmaking facilities, despite falling chip prices."

This paper analyzes investment decisions of firms in high-tech industries. Typical examples of high-tech industries are industries for electronic (consumer) products such as dvd players, LCD television sets, personal computers, MP3 players, photo cameras, mobile phones, and personal digital assistants. Prices for personal computers dropped very fast during the last decades. Delaying a purchase decision with one year thus implies that the same or even a better personal computer will be available for less money. The same holds for other products, as confirmed in the article on Samsung Electronics (The Economist, January 15th, 2005, p. 60)

"While electronic gadgets such as digital cameras, mobile phones and flat-screen televisions remain as popular as ever, prices are falling."

Another feature of this kind of industries is that high-tech products become obsolete more quickly, i.e. the economic lifetime of these products becomes shorter as time passes. As an example think of the quick increase in the number of megapixels in a digital photo camera. Every new generation of this product has more megapixels, which reduces demand for previous generations. From the production side it is known that there is considerable learning in the production process, implying that production costs are decreasing over time. We conclude that high-tech firms face sharply decreasing prices, rapid product changes, and decreasing production costs.

In addition, a lot of high-tech industries face a phenomenon called the crystal cycle (see also Mathews (2005)). During periods of high demand, firms invest heavily in expensive new plants. This drives prices and profits down, where the former increases quantities. As demand grows the process repeats itself. Mathews (2005) shows that in the period 1990 to 2003 there have been five of such crystal cycles in the LCD industry. The crystal cycle phenomenon is nicely illustrated in an article on the LCD industry in The Economist (July 24th, 2004, p. 53):

"But with record spending this year on new and more efficient LCD production plants, a surplus of capacity could emerge next year... "There is no doubt that pricing pressure will intensify as new factories come on line," says Katsuhiko Machida. the president of Japan's Sharp. But price cuts could help to boost demand further... Increased demand and more efficient plants could mean that profit margins start to recover in 2006-but that could tempt firms to invest in still more LCD plants..."

Real options theory is the appropriate tool to analyze investment decisions under uncertainty (see, e.g., Dixit and Pindyck (1994), Smit and Trigeorgis (2004)). In most real options models uncertainty is incorporated via a geometric Brownian motion (GBM) process (see, e.g., Schwartz and Zozaya-Gorostiza (2003) and Cortazar *et al.* (1998)). Departing from this theory, this paper analyzes the investment decisions of high-tech firms. After that we confront this theoretical framework with real life data. We find that, mainly due to the crystal cycle, the price development in the LCD market does not follow a GBM. For this reason we conduct a thorough econometric analysis, from which we conclude that a vector autoregressive (VAR)

process provides the best fit for the development of prices and costs in the LCD market. Incorporating such a VAR process in our model leads to a framework that, unfortunately, is not analytically tractable. Therefore we employ simulation to analyze the high-tech investment decisions.

From analyzing the data we conclude that at the time of an investment, the resulting capacity increase goes along with decreasing output price and increasing production cost. The decreasing output price is a result of the fact that the firm needs to attract additional customers in order to keep on using a considerable part of the increased capacity. Production costs are higher because learning is prominently present in this industry and operating a new generation LCD production facility in an efficient manner requires its own exclusive experience. Hence, installation of a new generation LCD production facility implies that a firm almost has to start all over with learning. This in turn implies that unit costs are high just after the firm starts producing with the new capital stock. In other words, although unit costs are decreasing in the long run, they jump up at every point of time that new capacity is taken into operation.

We also find that a decrease in prices is most of the time followed by a cost decrease. This can be seen as a management effect, where the management is pushing harder on cost decreasing programs when prices fall. See for example the following citation in The Economist's article on Samsung Electronics (The Economist, January 15th, 2005, p. 62):

"The prices of flat-screen televisions are also coming down as competition grows and capacity increases. A 32-inch LCD TV that would have sold for around $3800 in America in 2003, now fetches about $2400. Although lower prices expand the market, they also put pressure on producers to slash manufacturing costs in order to protect profit margins."

A main difference with GBM is that under VAR a decision to invest is based on the past development of prices and costs, so that the decision whether or not to invest can depend on the place of the current price in the crystal cycle. While analyzing investment decisions in five different generations of LCD plants, we find that this difference in approach leads to a different investment decision for three generations of LCD plants: under GBM it is not optimal to invest, while under VAR investing turns out to be optimal. Confronting our findings with the investment decisions taken in practice by a big international firm, we conclude that only two out of five decisions are supported by the GBM approach. In three cases the GBM model would have advised not to invest, while in practice the firm did invest. For VAR the score is five out of five. Another remarkable feature is that for some investment decisions it holds that they are approved by VAR, while at the same time the NPV is negative when calculated within the GBM model.

This paper is organized as follows. Besides this introduction there are four sections. Section 2 employs the standard real options approach, thus uncertainty modeled according to GBM, to analyze a high-tech investment decision. In Section 3 we confront this standard real options approach with real life data. Section 4 presents the VAR framework, while the last section concludes.

2 The Investment Model with Geometric Brownian Motion

Consider a firm that can undertake an irreversible investment by paying a sunk cost $I\,(>0)$. After the investment the firm can produce Q units of the product per time period. The price of the product at time t equals $P\,(t)$. Let $P\,(t)$ follow a GBM:

$$dP\,(t) = \alpha_P P\,(t)\,dt + \sigma_P P\,(t)\,d\omega_P\,(t)\,, \tag{1}$$

$$P\,(0) = P_0, \tag{2}$$

where α_P is a constant representing the trend, σ_P is a constant related to the uncertainty part of the GBM equation, while $d\omega_P(t)$ is the increment of a Wiener process implying that it is independently and normally distributed with mean 0 and variance dt. The discount rate is $r\,(>0)$.

The unit production cost is equal to $C(t)$, which also behaves according to a GBM:

$$dC(t) = \alpha_C C(t)\,dt + \sigma_C C(t)\,d\omega_C(t), \tag{3}$$

$$C(0) = C_0, \tag{4}$$

where the constants α_C and σ_C have an analogous interpretation as above, and the Wiener process $d\omega_C(t)$ is also independently and normally distributed with mean 0 and variance dt. Denoting the correlation coefficient between the two Wiener processes by ρ, we have that $E[d\omega_P d\omega_C] = \rho dt$.

The profit flow of the firm after the investment is denoted by $\pi(P(t), C(t))$ and is equal to

$$\pi(P(t), C(t)) = Q(P(t) - C(t)). \tag{5}$$

The expected present value that the firm obtains after it invests, can then be expressed as

$$V(P(t), C(t)) = E\left[\int_{s=t}^{\infty} \pi(P(s), C(s)) \exp(-rs)\,ds\right]. \tag{6}$$

From now on we omit the time dependence of the variables as long as there is no confusion possible. Concerning this value of the firm after the investment, the following proposition can be established (the proof is given in Appendix A.1).

Proposition 1 *Define the markup ratio as*

$$\tau = \frac{P}{C}. \tag{7}$$

Then the value of the firm after the investment equals

$$V(P, C) = C\nu(\tau) = CQ\left(\frac{\tau}{r - \alpha_P} - \frac{1}{r - \alpha_C}\right). \tag{8}$$

As long as the firm has not invested yet, it holds an option to invest. The value of the option to invest is denoted by $F(P, C)$ and is determined in the following proposition. The proof of the proposition can be found in Appendix A.2.

Proposition 2 *The value of the option to invest equals*

$$F(P, C) = C\phi(\tau), \tag{9}$$

in which

$$\phi(\tau) = B_1 \tau^{\beta_1}, \tag{10}$$

while $\beta_1\,(>1)$ is the positive root of

$$\frac{1}{2}\left(\sigma_P^2 - 2\rho\sigma_C\sigma_P + \sigma_C^2\right)\beta(\beta - 1) + (\alpha_P - \alpha_C)\beta - (r - \alpha_C) = 0. \tag{11}$$

Since both the value of the firm after the investment and the value of the option to invest are linear in C and further depend only on the price-cost ratio τ, analogous to Dixit and Pindyck (1994, Section 6.5), the optimal investment decision is completely governed by τ. This implies that a threshold value τ^* exists so that, whenever the price-cost ratio exceeds τ^*, it is optimal for the firm to invest immediately. Otherwise, it is optimal for the firm to wait with investment.

As is standard in real options theory (cf. Dixit and Pindyck (1994)), the threshold value τ^* can be found by employing the value matching and smooth pasting conditions, which can be obtained from (8) and (9):

$$C\phi(\tau^*) = C\nu(\tau^*) - I, \tag{12}$$

$$\left.\frac{\partial C\phi(\tau)}{\partial \tau}\right|_{\tau=\tau^*} = \left.\frac{\partial C\nu(\tau)}{\partial \tau}\right|_{\tau=\tau^*}. \tag{13}$$

Substitution of (10) and the right-hand side of (8) in (12) and (13) gives

$$CB_1\tau^{*\beta_1} = CQ\left(\frac{\tau^*}{r-\alpha_P} - \frac{1}{r-\alpha_C}\right) - I, \tag{14}$$

$$\beta_1 CB_1\tau^{*\beta_1-1} = \frac{CQ}{r-\alpha_P}. \tag{15}$$

It follows that

$$\tau^* = \frac{\beta_1}{\beta_1-1}\left(\frac{r-\alpha_P}{r-\alpha_C} + \frac{(r-\alpha_P)I}{CQ}\right). \tag{16}$$

3 LCD Industry

This section applies the model of the previous section to the LCD industry. In particular, we investigate five investment decisions of a company that is active in the LCD industry. As we argued in the Introduction, in such an industry the typical long run features are decreasing production costs and even more strongly decreasing prices.

Section 3.1 shortly discusses the industry. After that we describe the production process of such a company in Section 3.2. The data is presented and used for estimating the parameters in Section 3.3. In Section 3.4 we employ the econometric estimations to analyze the five investment decisions.

3.1 Industry

We focus on the industry of TFT-LCD[1] panel production. The companies that are active in this industry sell their products, i.e. LCD panels, to other companies (or other divisions of the same company). These other companies integrate the LCD panels into products like for example mobile phones, notebooks, monitors, and television sets.

Japanese firms (NEC, Sharp, Toshiba) started the LCD industry in the late 1980s. In the early 1990s South Korean firms (Samsung and Goldstar Inc., where the latter is the predecessor of LG.Philips LCD (LPL)) entered the market, followed by Taiwanese companies in the late 1990s (AU Optronics (AUO), Chi Mei Optoelectronics (CMO), Chunghwa Picture Tubes (CPT), Quanta Display Inc. (QDI), where the latter merged with AUO in the fall of 2006). Table 1 gives the ranking of LCD panel producers in November 2006.

[1] TFT is the abbreviation for Thin Film Transistor. TFT-LCD screens are a subset of all LCD screens. Other types of LCD screens are DSTN (Dualscan Super Twisted Nematics) and STN (Super Twisted Nematic) screens, for example. In the remainder of the paper we write LCD instead of TFT-LCD when there is no confusion possible.

Rank	Notebook	Monitor	TV	Total
1	LPL	Samsung	LPL	LPL
2	AUO	AUO	AUO	Samsung
3	Samsung	LPL	Samsung	AUO
4	CMO	CMO	CMO	CMO
5	CPT	CPT	Sharp	CPT

Table 1: LCD panel shipment ranking (unit basis) in November 2006. *Source: WitsView.*

3.2 Production Process

The most important characteristic of an LCD production facility is the size of the mother glass. The size of the mother glass, or substrate, determines the so-called generation of the production facility. For example, the 4th generation has a substrate size of 68 cm by 88 cm and was first operated by LG.Philips LCD in 2000. In 2005 Sharp announced that it plans to build an 8th generation LCD plant with a substrate size of 220 cm by 240 cm. As the LCD panels are cut out of the substrate, the substrate on the one hand determines which panel sizes can be produced and on the other hand how efficient each possible panel size can be produced. In this sense, every investment in a new generation implies a process and a product innovation. We have a process innovation, because a larger glass area provides a more efficient solution of the *cutting problem*, and thus cheaper costs in the production process. Product innovation arises, because the larger area of the substrate makes it possible to produce larger screens.

The substrate size that a company selects, heavily depends on the expectations that the company has about the prevailing standard sizes in the market. For example, Samsung and Sony are using a 7th generation plant with a substrate size of 187 cm by 220 cm, because they expect that 40 inch and 46 inch television screens will become the standard sizes. At the same time, LG.Philips LCD and Chi Mei Optoelectronics are aiming at 42 inch and 47 inch television sets with their 7th generation production facility of 195 cm by 225 cm.

3.3 Data and Estimations

The dataset is from one of the top 5 players in the LCD industry. For 32 quarters (from 1999Q1[2] up to and including 2006Q4) we have the average price and the average cost per squared meter LCD in the specific quarter. Moreover, during this time period the company made five investments in new production facilities, the details of which are presented in Table 2. Each new investment is in a new generation of the production facility. The substrate area, i.e. the size of glass in squared meters, increases with each new generation. To handle bigger substrates, larger machines, larger cleanrooms, and larger investments are required, as can be seen in Table 2.

In Figure 1 the dataset and the five investment moments are presented. This figure shows that after each moment of investment the price decreases (larger supply) and costs increase, where it should be taken into account that due to the time-to-build feature these phenomena can be observed some time after an investment is undertaken. The cost increase arises because of the presence of learning in the production process. The LCD industry experiences a so-called ramp up time (time needed to start a production line),

[2] We denote by 1999Q1 the first quarter of 1999.

Generation	Width (in cm)	Height (in cm)	Area (in m^2)	Monthly capacity (in 10^3 substrates)	Investment cost (times 10^6)	Decision
G4	68	88	0.598	60	1237	1999Q4
G5a	100	120	1.20	60	1635	2000Q2
G5b	110	125	1.38	60	1448	2002Q2
G6	150	185	2.78	90	3295	2003Q2
G7	195	225	4.39	90	5257	2004Q4

Table 2: Characteristics of the five investments.

with a strongly increasing yield (amount of good products relative to the total amount of products) in the first quarters after the start of production. This makes that costs are at their highest level just after starting the production process with new capital goods. Then, as time passes, costs decrease because of learning. Due to the fact that the time-to-build increases for each new generation, the time lag between the investment decision and the moment of the price decrease and cost increase becomes larger over the years. For example, for the 4th generation the time lag was approximately 2 quarters (1999Q4 to 2000Q2) while for the 6th generation it was 5 quarters (2003Q2 to 2004Q3).

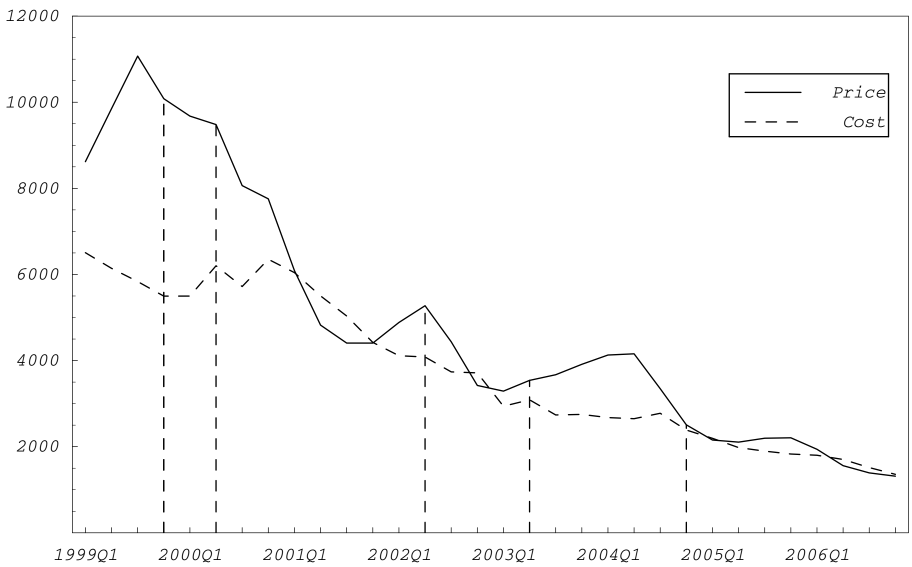


Figure 1: Quarterly average cost and average price per squared meter LCD over the period 1999Q1-2006Q4. Furthermore, the five investment moments are marked: 1999Q4 (G4), 2000Q2 (G5a), 2002Q2 (G5b), 2003Q2 (G6), and 2004Q4 (G7).

Most of the time the real options literature employs a *GBM* process to introduce uncertainty in the investment model, as we have done in the previous section. Using Ito's lemma we can rewrite equation (3) into

$$d\ln C\left(t\right)=\left(\alpha_C-\frac{1}{2}\sigma_C^2\right)dt+\sigma_C d\omega_C\left(t\right). \tag{17}$$

To work with the dataset, we discretize (17):

$$\ln C_t-\ln C_{t-1}=\left(\alpha_C-\frac{1}{2}\sigma_C^2\right)+\sigma_C\varepsilon_t, \tag{18}$$

where ε_t is assumed to be independently and normally distributed with mean zero and variance 1. Define logarithmic cost and price changes, and corresponding averages as $\kappa_t\equiv\ln C_t-\ln C_{t-1}$, $\lambda_t\equiv\ln P_t-\ln P_{t-1}$, $\overline{\kappa}=\frac{1}{T}\sum\limits_{t=1}^{T}\kappa_t$ and $\overline{\lambda}=\frac{1}{T}\sum\limits_{t=1}^{T}\lambda_t$, where T denotes the number of observations. For our dataset we have that $T=31$ (note that 32 observations lead to 31 cost (price) differences), and from these observations the following parameter estimations are derived:

$$\widehat{\sigma_C}=\sqrt{\frac{1}{T-1}\sum_{t=1}^{T}\left(\kappa_t-\overline{\kappa}\right)^2}=0.0728, \tag{19}$$

$$\widehat{\alpha_C}=\overline{\kappa}+\frac{1}{2}\widehat{\sigma_C}^2=-0.0479, \tag{20}$$

$$\widehat{\sigma_P}=\sqrt{\frac{1}{T-1}\sum_{t=1}^{T}\left(\lambda_t-\overline{\lambda}\right)^2}=0.121, \tag{21}$$

$$\widehat{\alpha_P}=\overline{\lambda}+\frac{1}{2}\widehat{\sigma_P}^2=-0.0533, \tag{22}$$

$$\widehat{\sigma_{PC}}=\frac{1}{T-1}\sum_{t=1}^{T}\left(\kappa_t-\overline{\kappa}\right)\left(\lambda_t-\overline{\lambda}\right)=0.00140, \tag{23}$$

$$\widehat{\rho}=\frac{\widehat{\sigma_{PC}}}{\widehat{\sigma_P}\widehat{\sigma_C}}=0.158. \tag{24}$$

As said before, the trend for both prices and costs is negative, while we also see that price uncertainty is more than 50 % larger than cost uncertainty.

3.4 Analysis

Combining the estimations (19)-(24) and the theoretical results of the previous section, we analyze the five investments in new production facilities. From equation (16) we can deduct that the firm should invest whenever the current price P exceeds $P^*\left(C\right)$, with C the current cost and

$$P^*\left(C\right)=\frac{\beta_1}{\beta_1-1}\left(C\frac{r-\alpha_P}{r-\alpha_C}+\frac{\left(r-\alpha_P\right)I}{Q}\right). \tag{25}$$

Additionally, we know that the expected NPV of the investment is positive whenever the current price P exceeds $P_{NPV}\left(C\right)$ (cf. Dixit and Pindyck (1994)), where

$$P_{NPV}\left(C\right)=\left(C\frac{r-\alpha_P}{r-\alpha_C}+\frac{\left(r-\alpha_P\right)I}{Q}\right). \tag{26}$$

Figure 2 compares these outcomes with the decisions that have been taken in practice. To do so, in this figure the functions (25) and (26) are depicted. Furthermore, we present a curve that connects the realized price and cost values around the quarter that the investment was undertaken. In each figure there are seven dots, each of which depicts the price and unit cost at a given quarter. In the middle quarter, i.e. the fourth one, the investment has been undertaken. From these figures we conclude that the investment decision in the 4th generation (panel (a) of Figure 2) is in line with the decision that our real options model prescribes. The first investment decision in the 5th generation should have been taken earlier, but this difference can occur because in practice it can take time to implement such an investment decision (panel (b) of Figure 2). However, the second investment in the 5th generation (panel (c) of Figure 2) and the investments in the 6th (panel (d) of Figure 2) and 7th generations (panel (e) of Figure 2) would not have been undertaken if our real options model was followed. Note that our real options model even predicts a negative NPV for the 6th and 7th generation investments.

We conclude that only two of the five investment decisions are taken optimally, seen from the perspective of our GBM real options model. This implies that either the firm was three times wrong in undertaking the investment, or that the data does not follow a GBM process which would imply the invalidity of our model. In the next section it is argued that in any case the latter is true.

4 The VAR Approach

Section 4.1 broadly describes the consecutive steps of the econometric analysis and its conclusions. The details of this analysis are presented in Appendix B. The main result, the estimated VAR model, is employed in Section 4.2 to analyze the same five investment decisions as in the previous section.

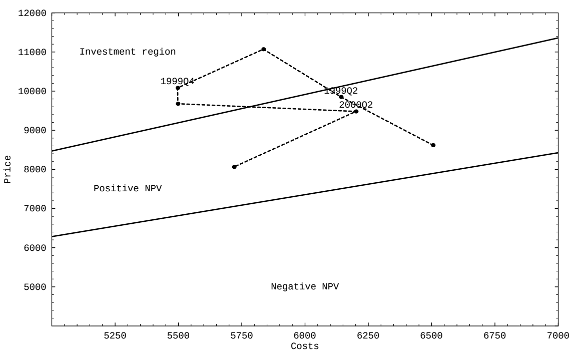
4.1 Econometric Analysis

In the previous section we fitted the discretization of the GBM, as presented in (18) for logarithmic costs and a similar equation for prices, on our dataset. Now we verify whether the resulting processes match with the data. To do so we conduct a systematic time series analysis, while using STATA/SE 9.2 for our calculations and Mathematica 5.2 to create the figures.

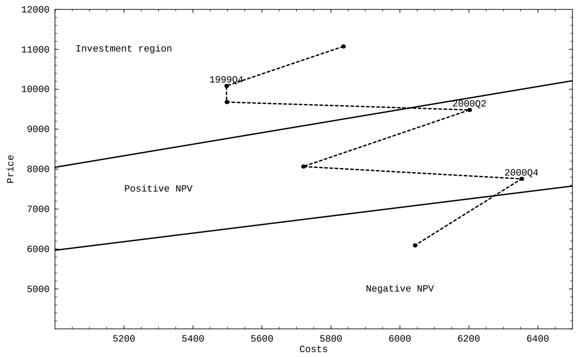
For a model with differences of logarithmic costs and prices as dependent variables to be stationary, the logarithmic costs and prices must have exactly one unit root each. In other words, if this is not the case the model in differences is not stationary and, consequently, a GBM process does not fit the data. The first step of our analysis is to test whether the logarithmic costs and prices actually have this property (see the online Appendix, which is referred to in Appendix B.1). After this extensive unit root analysis, we are able to conclude that both logarithmic costs and logarithmic prices have exactly one unit root. In other words, we can construct a stationary model for differences of logarithmic costs and prices.

The second step is to conduct a univariate time series analysis for the differences in logarithmic costs and logarithmic prices (see Appendix B.2). We compute the autocorrelation (AC) and partial autocorrelation (PAC) functions and find that there are no significant ACs and PACs for logarithmic cost changes. This implies that logarithmic costs indeed can be described by a GBM. However, for logarithmic prices the first two PACs changes are significant, which means that logarithmic prices follow an autoregressive model of order 2 ($AR(2)$) instead of a GBM.

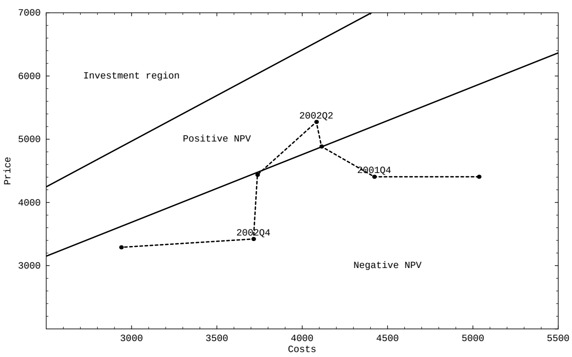
Thirdly, we investigate cointegration between logarithmic costs and logarithmic prices and *ex-ante* causality between these variables (see Appendix B.3). Applying Granger's causality test gives the following two results: (1) both null hypotheses that there is no causality from logarithmic prices to logarithmic costs and the reverse are strongly rejected when taking two or more lags into consideration and (2) the null hypothesis that there is no causality from logarithmic costs to logarithmic prices is rejected with one lag, but the reverse



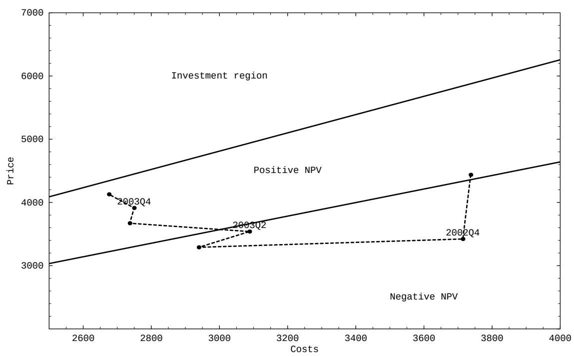
(a) G4



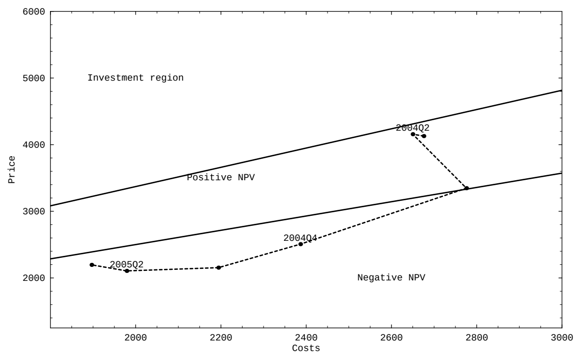
(b) G5a



(c) G5b



(d) G6



(e) G7

Figure 2: Investment regions for the 4th (G4), the first 5th (G5a), the second 5th (G5b), the sixth (G6), and the 7th generation (G7) investments.

hypothesis is not rejected. On the basis of our analysis we can conclude that a tendency of causality from lagged prices to current costs can slightly, but not clearly, be observed. In fact, we may observe a high degree of *feedback* between costs and prices. Hence, we have to construct a multivariate structural vector autoregressive ($SVAR$) model.

The fourth step is the multivariate time series analysis (see Appendix B.4). We start with an unrestricted $SVAR(2)$ model[3]:

$$\begin{pmatrix} 1 & d_{12} \\ d_{21} & 1 \end{pmatrix} \begin{pmatrix} \kappa_t \\ \lambda_t \end{pmatrix} = \begin{pmatrix} a_1 \\ a_2 \end{pmatrix} + \begin{pmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{pmatrix} \begin{pmatrix} \kappa_{t-1} \\ \lambda_{t-1} \end{pmatrix} + \begin{pmatrix} c_{11} & c_{12} \\ c_{21} & c_{22} \end{pmatrix} \begin{pmatrix} \kappa_{t-2} \\ \lambda_{t-2} \end{pmatrix} + \begin{pmatrix} \varepsilon_{\kappa t} \\ \varepsilon_{\lambda t} \end{pmatrix}, \quad (27)$$

where $\varepsilon_{\kappa t}$ and $\varepsilon_{\lambda t}$ are identical and independently distributed variables with mean 0 and covariance matrix equal to

$$\begin{pmatrix} \sigma_\kappa^2 & \sigma_{\kappa\lambda} \\ \sigma_{\kappa\lambda} & \sigma_\lambda^2 \end{pmatrix}. \quad (28)$$

In STATA we can only estimate equation (27) if we pose a restriction either on d_{12} or d_{21}. Therefore, we fit (27) for two cases. In the first case we impose $d_{21} = 0$ and in the second case we have $d_{12} = 0$. We employ the general-to-specific approach, which implies that we introduce more zero constraints when coefficients are not significant. The contemporaneous values of logarithmic cost differences (d_{21}) and logarithmic price differences (d_{12}) disappear quickly. Ultimately we arrive at the following $VAR(2)$ model:

$$\begin{pmatrix} \widehat{\kappa}_t \\ \widehat{\lambda}_t \end{pmatrix} = \begin{pmatrix} 0 \\ \underset{(0.0176)}{-0.0807} \end{pmatrix} + \begin{pmatrix} 0 & \underset{(0.0791)}{0.369} \\ \underset{(0.198)}{-0.648} & \underset{(0.133)}{0.672} \end{pmatrix} \begin{pmatrix} \kappa_{t-1} \\ \lambda_{t-1} \end{pmatrix} + \begin{pmatrix} \underset{(0.125)}{0.575} & 0 \\ 0 & \underset{(0.133)}{-0.360} \end{pmatrix} \begin{pmatrix} \kappa_{t-2} \\ \lambda_{t-2} \end{pmatrix}. \quad (29)$$

The covariance matrix of the residuals in this model is given by

$$\begin{pmatrix} \widehat{\sigma}_\kappa^2 & \widehat{\sigma}_{\kappa\lambda} \\ \widehat{\sigma}_{\kappa\lambda} & \widehat{\sigma}_\lambda^2 \end{pmatrix} = \begin{pmatrix} 0.00334 & 0.000264 \\ 0.000264 & 0.00543 \end{pmatrix}. \quad (30)$$

From equations (27) and (29) we can conclude the following. In the case of GBM the parameters b_{ij} and c_{ij} ($i, j \in \{1, 2\}$) are zero, implying that under GBM P_t only depends on P_{t-1}. However, now we obtain that for the LCD industry we need the values of P_{t-1}, P_{t-2} and P_{t-3} to come up with the best possible estimate for the current price. This seems to point to the existence of a crystal cycle, where it is not enough to know just P_{t-1} in order to determine P_t. Instead the values of P_{t-1}, P_{t-2} and P_{t-3} are needed to determine the "location" of P_t in the cycle.

A second interesting feature is the rampup effect of large capacities ($b_{21} < 0$). While ramping up a new plant a firm temporarily faces increasing production costs and lower prices. The latter holds, because increased capacity leads to more production and to sell the extra production, prices have to be lowered. Furthermore, right after the moment of the investment, new capital goods will be used in the production process. It requires experience to produce efficiently with a new generation of the production technology. Therefore, in the beginning production costs will be high, while they will decrease over time due to the process of learning. Furthermore, we see a management effect ($b_{12} > 0$), i.e. a price drop is followed by a cost decrease due to management pushing harder on cost decreasing programs. Finally, after comparing (30) with (19) and (21) we conclude that under VAR the variance is lower than under GBM. This is because the VAR model explains more of the underlying price and cost processes.

[3] Note that the order 2 is a result of the univariate time series analysis.

In the last step (see Appendix B.5) we study *ex-post* causality based on the estimated VAR model (29). We find that there is a a very strong *ex-post* causality in both directions. In other words, we observe a very strong feedback between costs and prices.

4.2 Simulations

We apply Monte Carlo simulation to the VAR model of equation (29) to estimate the expected NPV and the expected option value of the five capacity investments that were discussed in the previous section. After having determined this, we employ the investment criterion known from the real options theory (cf. Dixit and Pindyck (1994)) to take the optimal investment decision. This criterion says that it is optimal to invest whenever the NPV equals the value of the option to invest (value matching). Note that option values are always positive, which implies that a positive NPV is a necessary condition for an investment to be optimally undertaken.

Like we did in Figure 2, for each investment decision we consider the seven consecutive quarters around the time the investment was undertaken in practice. For each quarter we determine the NPV of the investment given that it was undertaken right at that quarter. We use the realized prices (costs) of that quarter and the previous quarter as a starting point for the simulation (remember that λ_t occurs in (29), where $\lambda_t \equiv \ln P_t - \ln P_{t-1}$, while for the costs an analogous story holds). In each simulation run we simulated the prices and the costs 100 quarters into the future.

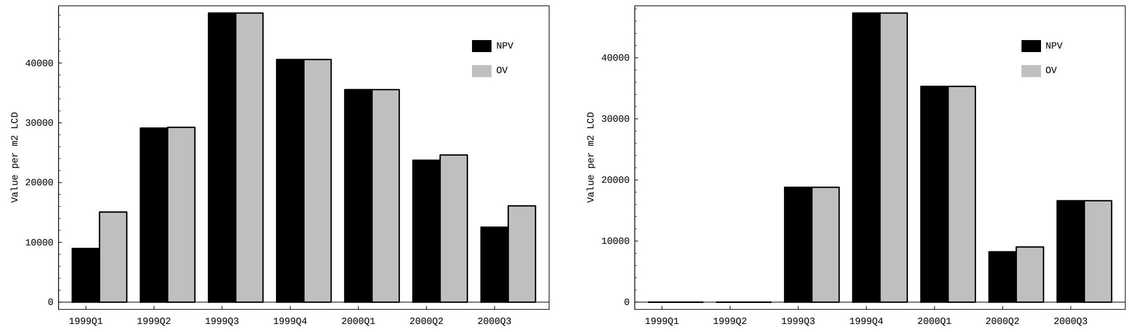
Employing dynamic programming we determine the value of the option to invest. Starting at the end of the simulation path and working backwards in time, for each simulated quarter the value of investing and not investing, i.e. waiting with investing at least until the next quarter and acting optimally in choosing the investment time from thereon, is calculated. In this way we find for each simulation path the optimal investment strategy and the option value. The expected NPV and the expected value of the option are determined by taking the average over 1 million simulation paths.

In the Figures 3-7 the results of the simulations of the five investment decisions are presented in the bar charts on the right-hand side. Furthermore, for reasons of comparison we present the results for the GBM model on the left-hand side. Applying the real options investment decision rule we know that, whenever the NPV bar is lower than the option value (OV) bar, it is better to keep the investment option alive by waiting. In such a case it is thus better to refrain from investing. However, when these bars are of equal height, it is optimal to invest.

While comparing the figures for the five investment decisions, we draw the conclusion that the VAR and the GBM models lead to the same investment decision for the investments in the 4th and the first 5th generation. However, we see different recommendations for the investments in the second 5th, the 6th and the 7th generation plant: whereas the GBM model suggests not to invest, the VAR model gives a positive advise. The VAR approach in fact supports the investments in the second 5th, the 6th and the 7th generation that were undertaken in practice. It is interesting to notice that in some cases it is optimal to invest when applying the VAR model, while in fact at the same time the NPV is negative under GBM (see, e.g., Figure 5).

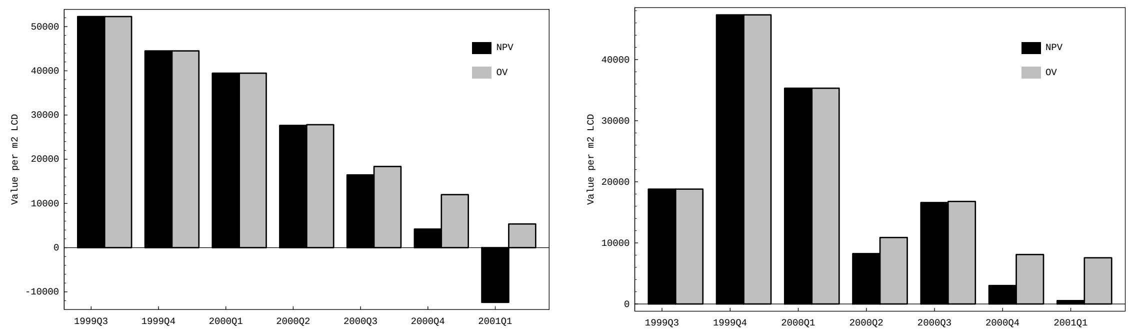
5 Conclusion

This paper considers investments in high-tech industries, which are characterized by rapid innovations, decreasing prices, price uncertainty, and cost learning curves. The appropriate tool to analyze investment



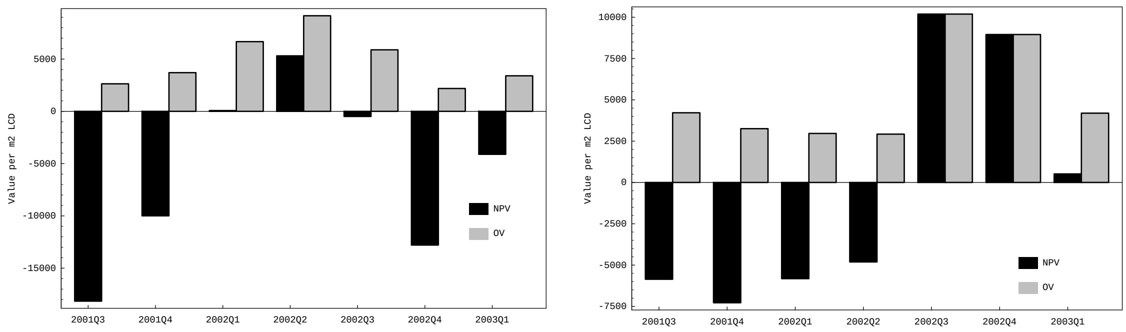
(a) GBM (b) VAR

Figure 3: Net present value (NPV) and option value (OV) for the 4th generation investment with GBM and VAR. Investment is optimal in quarters 1999Q3, 1999Q4, 2000Q1, and 2000Q3 according to the VAR model.



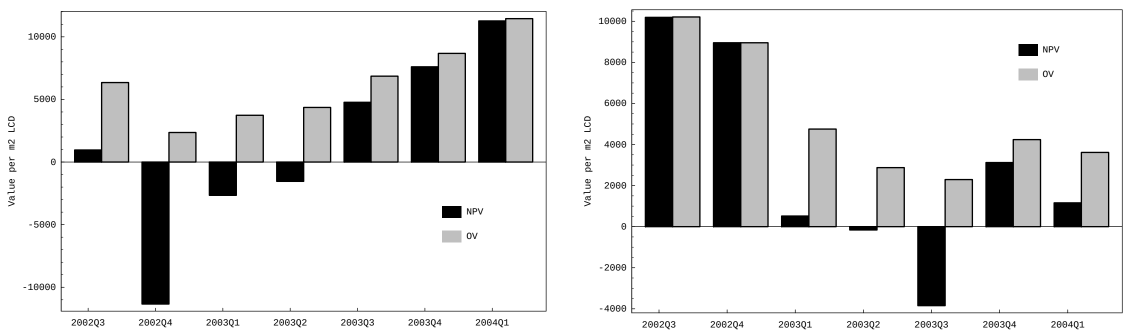
(a) GBM (b) VAR

Figure 4: Net present value (NPV) and option value (OV) for the first 5th generation investment with GBM and VAR. Investment is optimal in quarters 1999Q3, 1999Q4, and 2000Q1 according to the VAR model.



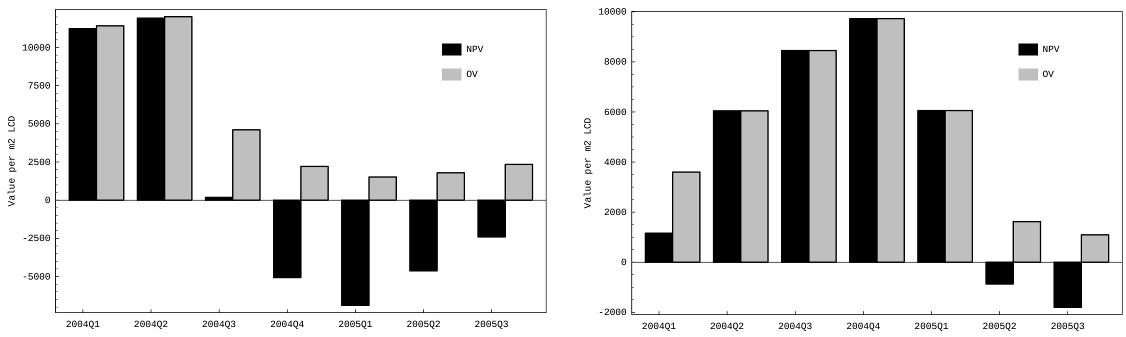
(a) *GBM* (b) *VAR*

Figure 5: Net present value (NPV) and option value (OV) for the second 5th generation investment with *GBM* and *VAR*. Investing is optimal in quarters 2002Q3 and 2002Q4 according to the *VAR* model.



(a) *GBM* (b) *VAR*

Figure 6: Net present value (NPV) and option value (OV) for the 6th generation investment with *GBM* and *VAR*. Investing is optimal in quarter 2002Q4 according to the *VAR* model.



(a) GBM (b) VAR

Figure 7: Net present value (NPV) and option value (OV) for the 7th generation investment with GBM and VAR. Investing is optimal in quarters 2004Q2, 2004Q3, 2004Q4, and 2005Q1 according to the VAR model.

decisions is real options theory. For this reason we start out applying a standard real options approach where prices and costs follow a geometric Brownian motion process (GBM). We confronted our findings with some recent data taken from the LCD (liquid crystal display) industry, which consists not only of price and cost developments, but also of five investments that were undertaken in practice. In this industry investment costs are huge due to the very advanced technology involved. For this reason it is important to choose the right investments and to undertake these investments at the right time. We found that out of the five investments undertaken in practice, the standard real options approach concluded that only two of them were optimal.

However, we also found that the price development in this industry does not behave according to a GBM process. The reason is that prices follow a so-called crystal cycle, which implies that to estimate the price in the next period, it is not enough to base this estimate only on the current price, as is the case under GBM. We found that a vector autoregressive model (VAR) provides a better fit, because such an approach makes it possible to let the price estimate depend on prices in the three previous periods.

The logical next step was to study the LCD industry investment decisions, while imposing that prices and costs follow a VAR model. However, after integrating the VAR model and the real options machinery it was not possible to find analytical solutions. Instead, we applied simulation and found that GBM and VAR lead to the same recommendations in two out of five cases in the sense that these two investment decisions taken in practice are supported by both methods. The other three investment decisions taken in practice are only supported by the VAR approach and not by GBM. Hence, the VAR approach fully supports the practical investment decisions.

Another conclusion of this paper is that real options theory should not rely too much on geometric Brownian motion. It seems to be worthwhile to extend this theory by integrating it with other dynamic stochastic processes.

What is missing in the framework of this paper is on the one hand the presence of competition and on the other hand time-to-build. High-tech industries like the LCD industry are oligopolistic industries where a few large firms are the major players. Then investments certainly have strategic aspects, where under specific circumstances it pays to preempt competitors in choosing the optimal investment timing. There are some recent contributions in real options theory (e.g. Grenadier (2000), Huisman (2001), Pawlina and

Kort (2006)) that may provide the tools to extend the present framework to allow for competitive behavior. Building a new LCD plant takes years, and therefore it would be more realistic to include time-to-build in the framework. Majd and Pindyck (1987) and Bar-Ilan and Strange (1996) can be the starting points for this extension.

A Proofs

A.1 Proof of Proposition 1

The Bellman equation that V must satisfy is given by

$$rV(P,C) = \pi(P,C) + \lim_{dt \downarrow 0} \frac{1}{dt} E[dV(P,C)]. \tag{31}$$

Expanding $E[dV(P,C)]$ with Ito's lemma gives

$$\begin{aligned} E[dV(P,C)] &= \alpha_C C \frac{\partial V(P,C)}{\partial C} dt + \alpha_P P \frac{\partial V(P,C)}{\partial P} dt \\ &+ \frac{1}{2}\sigma_C^2 C^2 \frac{\partial^2 V(P,C)}{\partial C^2} dt + \rho\sigma_C\sigma_P PC \frac{\partial^2 V(P,C)}{\partial P \partial C} dt + \frac{1}{2}\sigma_P^2 P^2 \frac{\partial^2 V(P,C)}{\partial P^2} dt. \end{aligned} \tag{32}$$

After substitution of (5) and (32) into (31) it holds that

$$\begin{aligned} rV(P,C) &= Q(P-C) + \alpha_C C \frac{\partial V(P,C)}{\partial C} + \alpha_P P \frac{\partial V(P,C)}{\partial P} \\ &+ \rho\sigma_C\sigma_P PC \frac{\partial^2 V(P,C)}{\partial P \partial C} + \frac{1}{2}\sigma_C^2 C^2 \frac{\partial^2 V(P,C)}{\partial C^2} + \frac{1}{2}\sigma_P^2 P^2 \frac{\partial^2 V(P,C)}{\partial P^2}. \end{aligned} \tag{33}$$

From (5) and (6) we obtain that the value of the firm is homogeneous of degree 1 in (P,C). Therefore, the optimal investment decision is only dependent on the markup ratio $\tau = \frac{P}{C}$. It holds that

$$V(P,C) = C\nu\left(\frac{P}{C}\right) = C\nu(\tau), \tag{34}$$

where $\nu(\tau)$ is now the function to be determined (see Dixit and Pindyck (1994, p. 210) for a similar argument). Differentiating (34) gives

$$\frac{\partial V(P,C)}{\partial C} = \nu(\tau) - \tau \frac{\partial \nu(\tau)}{\partial \tau}, \tag{35}$$

$$\frac{\partial V(P,C)}{\partial P} = \frac{\partial \nu(\tau)}{\partial \tau}, \tag{36}$$

$$\frac{\partial^2 V(P,C)}{\partial P \partial C} = -\frac{\tau}{C} \frac{\partial^2 \nu(\tau)}{\partial \tau^2}, \tag{37}$$

$$\frac{\partial^2 V(P,C)}{\partial C^2} = \frac{\tau^2}{C} \frac{\partial^2 \nu(\tau)}{\partial \tau^2}, \tag{38}$$

$$\frac{\partial^2 V(P,C)}{\partial P^2} = \frac{1}{C} \frac{\partial^2 \nu(\tau)}{\partial \tau^2}. \tag{39}$$

Substitution of equations (35)-(39) into equation (33) ultimately leads to

$$(r-\alpha_C)\nu(\tau) = Q(\tau-1) + (\alpha_P - \alpha_C)\tau \frac{\partial \nu(\tau)}{\partial \tau} + \frac{1}{2}\left(\sigma_P^2 - 2\rho\sigma_C\sigma_P + \sigma_C^2\right)\tau^2 \frac{\partial^2 \nu(\tau)}{\partial \tau^2}. \tag{40}$$

The general solution of (40) is

$$\nu(\tau) = A_1\tau^{\beta_1} + A_2\tau^{\beta_2} + Q\left(\frac{\tau}{r-\alpha_P} - \frac{1}{r-\alpha_C}\right), \tag{41}$$

where β_1 and β_2 are the roots of the following quadratic equation:

$$\frac{1}{2}\left(\sigma_P^2 - 2\rho\sigma_C\sigma_P + \sigma_C^2\right)\beta^2 + \left(\alpha_P - \alpha_C - \frac{1}{2}\left(\sigma_P^2 - 2\rho\sigma_C\sigma_P + \sigma_C^2\right)\right)\beta - (r - \alpha_C) = 0. \tag{42}$$

Analogous to Dixit and Pindyck (1994), we can prove that $\beta_1 > 1$ and $\beta_2 < 0$. Since $\nu(0) = 0$ and $\lim_{\tau\to\infty} \nu(\tau) = Q\left(\frac{\tau}{r-\alpha_P} - \frac{1}{r-\alpha_C}\right)$, it must hold that $A_1 = 0$ and $A_2 = 0$. This implies that

$$\nu(\tau) = Q\left(\frac{\tau}{r - \alpha_P} - \frac{1}{r - \alpha_C}\right). \tag{43}$$

A.2 Proof of Proposition 2

$F(P, C)$ must satisfy the following Bellman equation:

$$rF(P, C) = \lim_{dt\downarrow 0} \frac{1}{dt} E\left[dF(P, C)\right]. \tag{44}$$

Applying Ito's lemma to $E[dF(P, C)]$ and substitution of the result in (44) gives the following differential equation:

$$\begin{aligned} rF(P, C) = {} & \alpha_C C \frac{\partial V(P, C)}{\partial C} + \alpha_P P \frac{\partial V(P, C)}{\partial P} \\ & + \rho\sigma_C\sigma_P PC \frac{\partial^2 V(P, C)}{\partial P \partial C} + \frac{1}{2}\sigma_C^2 C^2 \frac{\partial^2 V(P, C)}{\partial C^2} + \frac{1}{2}\sigma_P^2 P^2 \frac{\partial^2 V(P, C)}{\partial P^2}. \end{aligned} \tag{45}$$

To solve this differential equation, we employ the same arguments as in the proof of Proposition 1. We thus notice that the value of the option to invest is only dependent on the ratio $\tau = \frac{P}{C}$ and the value of the option to invest is homogeneous of degree 1 in (P, C), so that

$$F(P, C) = C\phi\left(\frac{P}{C}\right) = C\phi(\tau), \tag{46}$$

where $\phi(\tau)$ is the function to be determined. Differentiating (46) gives

$$\frac{\partial F(P, C)}{\partial C} = \phi(\tau) - \tau \frac{\partial \phi(\tau)}{\partial \tau}, \tag{47}$$

$$\frac{\partial F(P, C)}{\partial P} = \frac{\partial \phi(\tau)}{\partial \tau}, \tag{48}$$

$$\frac{\partial^2 F(P, C)}{\partial P \partial C} = -\frac{\tau}{C}\frac{\partial^2 \phi(\tau)}{\partial \tau^2}, \tag{49}$$

$$\frac{\partial^2 F(P, C)}{\partial C^2} = \frac{\tau^2}{C}\frac{\partial^2 \phi(\tau)}{\partial \tau^2}, \tag{50}$$

$$\frac{\partial^2 F(P, C)}{\partial P^2} = \frac{1}{C}\frac{\partial^2 \phi(\tau)}{\partial \tau^2}. \tag{51}$$

Substitution of equations (47)-(51) into equation (45), dividing by C and rewriting leads to

$$(r - \alpha_C)\phi(\tau) = (\alpha_P - \alpha_C)\frac{\partial \phi(\tau)}{\partial \tau} + \frac{1}{2}\left(\sigma_P^2 - 2\rho\sigma_C\sigma_P + \sigma_C^2\right)\tau^2 \frac{\partial^2 \phi(\tau)}{\partial \tau^2}. \tag{52}$$

The general solution of equation (52) is equal to

$$\phi(\tau) = B_1 \tau^{\beta_1} + B_2 \tau^{\beta_2}, \tag{53}$$

where β_1 and β_2 are the positive and negative roots of equation (42). The option to invest will be worthless if the price equals zero, i.e. $\phi(0) = 0$. Therefore, it must hold that $B_2 = 0$.

B Econometrics

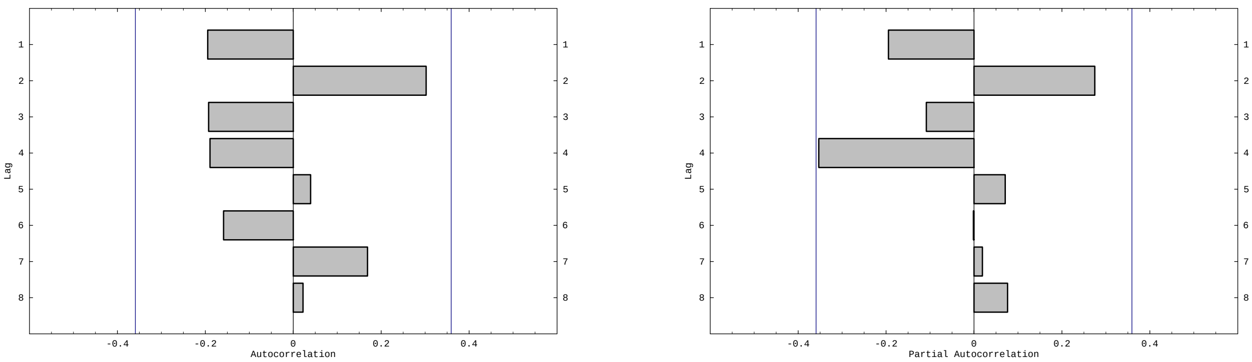
This appendix describes the econometric analysis in detail. The first step is to verify whether logarithmic costs and logarithmic prices have exactly one unit root each (Appendix B.1). This is a prerequisite for modelling costs and prices by a GBM. The second step is to conduct univariate time series analysis (Appendix B.2). Thirdly, we investigate cointegration between costs and prices and *ex-ante* causality (Appendix B.3). The fourth step is the multivariate time series analysis provided that there is no clear *ex-ante* causality (Appendix B.4), while in the last step (Appendix B.5) we study *ex-post* causality.

B.1 Unit Roots

An extensive unit root analysis is provided in the online appendix. The conclusion is that both logarithmic costs and logarithmic prices contain one unit root.

B.2 Time series estimates of logarithmic cost and price changes

From the unit root analysis we can conclude that we can determine univariate time series properties from the correlogram of differences in logarithmic costs and prices. The first step is to inspect the autocorrelations (ACs) and partial autocorrelations (PACs) of the differences in logarithmic costs and prices in case they are modeled according to a (discrete-time) GBM (cf. 18). We directly observe from the correlograms for the sample period 1999Q1-2006Q4 in Figures 8 and 9 that neither AC nor PAC is statistically significant at the 1% or 5% level for logarithmic cost differences, but that the first two PACs for the logarithmic price differences are statistically significantly different from zero. This is a result of the fact that the standard error of any (P)AC is $\frac{1}{\sqrt{T}}$ (see e.g. Plasmans (2006, pp. 70-71)), which yields in our case that $\frac{1}{\sqrt{31}} = 0.180$.



(a) ACs

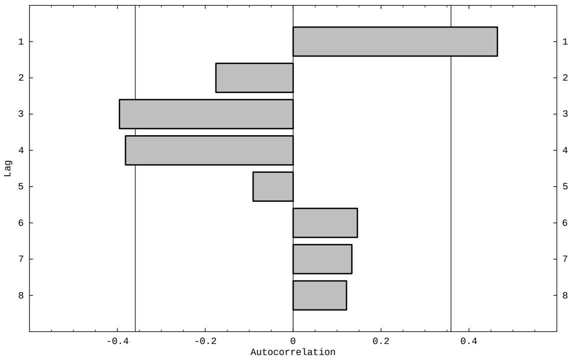
(b) PACs

Figure 8: ACs and PACs for the differences in logarithmic costs.

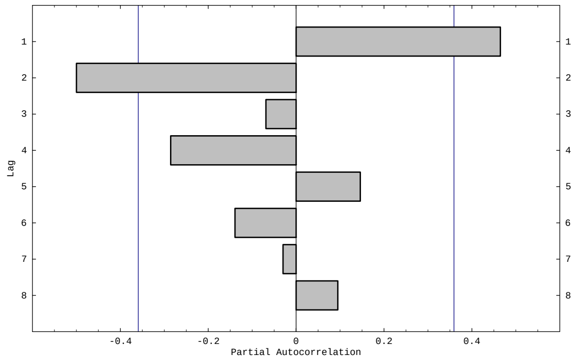
We conclude that logarithmic costs behave according to a GBM, while logarithmic prices are (at first instance) better described by an autoregressive model of order 2 ($AR(2)$). The results of the corresponding estimations are depicted in Table 3.

In the model for logarithmic prices the two estimated AR parameters and the intercept are statistically significant at the 1% level. Now, the resulting residuals

$$\widehat{\varepsilon}_t \equiv \lambda_t + 0.0572 - 0.668\lambda_{t-1} + 0.489\lambda_{t-2}, \tag{54}$$



(a) ACs



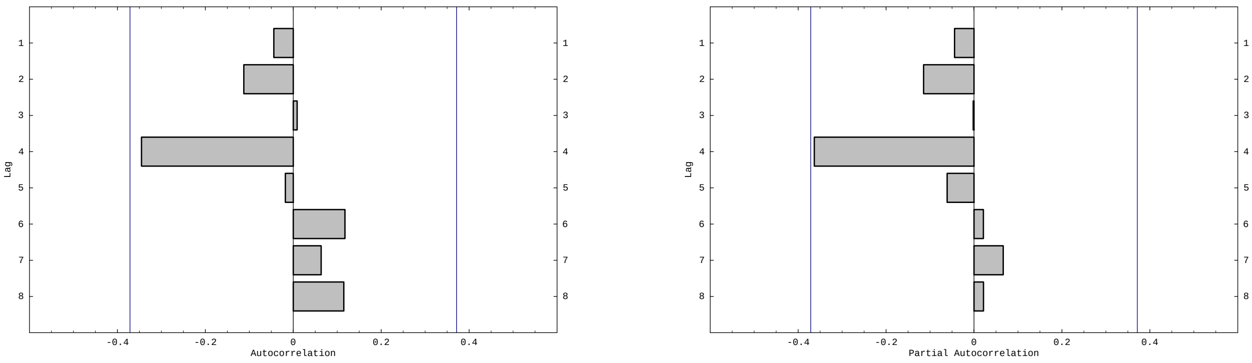
(b) PACs

Figure 9: ACs and PACs for the differences in logarithmic prices.

$\widehat{\alpha}$	estimation	
	κ_t	λ_t
$\widehat{\alpha_0}$	-0.0505^{**} (0.0131)	-0.0572^{**} (0.0200)
$\widehat{\alpha_1}$	-	0.668^{**} (0.165)
$\widehat{\alpha_2}$	-	-0.489^{**} (0.158)
R^2	0.00	0.408
AIC	-73.5	-53.5
BIC	-72.0	-49.4

Table 3: Estimation of a discrete GBM for differences in logarithmic costs (κ_t) and an $AR(2)$ for differences in logarithmic prices (λ_t).

must be analyzed to check their (remaining) autocorrelation behavior (diagnostic checking). Figure 10 presents the correlogram for the residuals, and we conclude that none of the residual ACs and PACs are statistically significant.[4] This confirms that the $AR(2)$ is the appropriate time series representation for the differences in logarithmic prices and a discrete-time GBM for prices is definitely rejected.



(a) ACs

(b) PACs

Figure 10: ACs and PACs for the residuals of the $AR(2)$ estimation for the differences in logarithmic prices.

B.3 Cointegration and causality between logarithmic costs and prices

Departing from the univariate time series properties of logarithmic costs and prices derived in the previous sections, we now analyze the short- and long-term time-dependency or the cointegration between these two variables. Once cointegration between logarithmic costs and prices can be established, causality should be analyzed. We have already verified that there is a unit root in both logarithmic cost and price series. Moreover, a simple linear regression shows that there is a clear relationship between logarithmic costs and prices

$$\ln \widehat{C}_t = \underset{(0.0475)}{0.752} \ln P_t + \underset{(0.396)}{1.87} \qquad \text{with} \quad R^2 = 0.893. \tag{55}$$

According to Engle and Granger (1987) there is cointegration between logarithmic costs and logarithmic prices, if the residuals $\widehat{\varepsilon}_t$ from the regression in (55) are stationary. Applying a Dickey-Fuller (DF) test to these regression residuals, we find a DF test statistic of -1.96, which lies in between the 1% and 5% critical values ($-2.65 < -1.96 < -1.95$). Hence, these residuals are integrated at the 1% level but not at the 5% level. However, we need to be sure that we included a sufficient number of lags in $\Delta\widehat{\varepsilon}_t = \vartheta_1 \widehat{\varepsilon}_{t-1} + \eta_t$,[5] to make the error term η_t white noise. Therefore, it is advisable to perform a range of ADF tests, in the sense that we add additional lags $\Delta\widehat{\varepsilon}_{t-i}$ $(i = 1, 2, 3, ...)$ to the right hand side of this error correction model (ECM) equation. Adding up to 4 lags in a sequential way results each time in a t statistic for $\widehat{\vartheta}_1$, which for each number of additional lags is the corresponding $(A)DF$ (test) statistic in Table 4. We observe that for ECMs with one and two lags the nonstationarity hypothesis of the residuals is rejected at 1% so that, although neither of the original (lags of) costs and prices is stationary, there is a linear combination of them

[4]Note that for these residuals we have that $T = 29$, so that $\frac{2}{\sqrt{T}} = 0.371$.

[5]This error correction model (ECM) regression is also called the ADF regression if there is at least one lag of $\Delta\widehat{\varepsilon}_t$ (and DF regression if there are no lags).

that is stationary. It can be concluded that logarithmic costs and prices are cointegrated with a long-term or cointegrating relationship (55).[6]

Additional lags	Number of observations	$(A)DF$ statistic	1% critical value	5% critical value
0	31	−1.96	−2.65	−1.95
1	30	−2.74	−2.65	−1.95
2	29	−2.95	−2.65	−1.95
3	28	−1.87	−2.66	−1.95
4	27	−1.64	−2.66	−1.95

Table 4: $(A)DF$ test statistics based on various first order ECMs for the residuals from (55).

Since a single cointegrating relation between logarithmic costs and logarithmic prices is found, we can investigate the (long-term) causality between these two variables by applying a Granger (1969) causality test. Describing the conditional probability density function of a stochastic variable y_t given its previous value and the previous occurrence of another variable by $f(y_t|\, y_{t-1}, x_{t-1})$, we have *Granger noncausality* in the sense that x does not cause y if $f(y_t|\, y_{t-1}, x_{t-1}) = f(y_t|\, y_{t-1})$. Hence, x causes y at period t if the past of x provides additional information for the forecast of y_t, compared to considering the past of y alone.

There are various specific versions of a Granger causality test:

- Sims (1972): If (x_t, y_t) is a 2-dimensional time series, then Sims's version of Granger's causality test is based on the regression of y_t on previous and future values of x_t:

$$y_t = \sum_{i=n}^{-m} \gamma_{-i} x_{t-i} + \upsilon_t. \tag{56}$$

  A test that y does not cause x is a conventional F test, in the case of a sufficiently large number T of observations, for the null hypothesis $\gamma_1 = \gamma_2 = ... = \gamma_m = 0$ with m and $T - m - n$ degrees of freedom. There may still be serial correlation in the error term υ_t.

- Geweke *et al.* (1983): it is assumed that υ_t can be approximated by an $AR\,(p)$ process:

$$y_t = \sum_{j=1}^{p} \phi_{-j} y_{t-j} + \sum_{i=n+p}^{-m} \gamma_{-i} x_{t-i} + u_t, \tag{57}$$

  i.e. a regression of y on p past values of y, m future values of x and $(n + p)$ past values of x with the null hypothesis that y does not cause x, or $\gamma_1 = \gamma_2 = ... = \gamma_m = 0$. This can be tested by a traditional

[6] It should be noted that, although the OLS residuals from (55) have obviously zero mean when considered over the whole sample, estimating an ECM equation involves a loss of $p + 1$ observations when there are $p = 0, 1, 2, 3$ or 4 (additional) lags, so that a constant term ϑ_0 in the ECM equation would trivially differ from zero and testing nonstationarity with drift should be made (with lower critical values) in a finite sample. However, given the about 30 observations in our case, this constant is found to be of very small size and not statistically significant at all, i.e. having values with standard errors between brackets below as follows: $\underset{(0.0185)}{-0.00449}$ without lags, $\underset{(0.0169)}{0.00107}$ for one lag, $\underset{(0.0171)}{0.00487}$ for two lags, $\underset{(0.0178)}{0.00241}$ for three lags, and $\underset{(0.0190)}{0.00363}$ for four lags. The $(A)DF$ statistics became higher than in Table 4 (−1.92, −2.69, −2.90, −1.84, and −1.61 for 0, 1, . . . , 4 lags, respectively) with lower critical values so that the null of nonstationarity was nowhere rejected, even at 5%. Given the completely insignificant very small constants, however, we decided not to consider the occurrence of such a constant term in the ECM regression.

F test, in the case of a sufficiently large number T of observations, with m and $T-m-n-2p$ degrees of freedom.

However, Monte Carlo simulations in Geweke *et al.* (1983) and Geweke (1984) with specification (57) suggest that the simple and most straightforward F test, which is based on the unrestricted model

$$y_t = \alpha_0 + \sum_{j=1}^{p} \alpha_j y_{t-j} + \sum_{i=1}^{m} \beta_i x_{t-i} + u_t,$$

should be employed by testing under the null that $\beta_1 = \beta_2 = \ldots = \beta_m = 0$. Following Hamilton (1994, pp. 304-305), the STATA software sets $m = p$. The corresponding test results are presented in Table 5, where the F statistics have $p = 1, 2, 3, 4$ and $T - 2p - 1 = 28, 25, 22, 19$ degrees of freedom. From this table it becomes clear that both null hypotheses that logarithmic prices do not cause logarithmic costs and the reverse are rejected when taking two or more lags into consideration. The null hypothesis that logarithmic costs do not cause logarithmic prices is not rejected with one lag, while the reverse hypothesis is rejected. We conclude that a tendency of causality from lagged prices to current costs can slightly, but not clearly, be observed (*ex-ante*). In fact, we may observe a high degree of *feedback* between costs and prices. Hence, we have to construct a multivariate structural vector autoregressive ($SVAR$) model.[7]

Null Hypothesis	# lags	# obs.	F statistic	Excess probability
$\ln P$ does not Granger-cause $\ln C$	1	31	14.8	0.0006
$\ln C$ does not Granger-cause $\ln P$	1	31	0.00	0.9548
$\ln P$ does not Granger-cause $\ln C$	2	30	11.5	0.0003
$\ln C$ does not Granger-cause $\ln P$	2	30	7.31	0.0032
$\ln P$ does not Granger-cause $\ln C$	3	29	9.40	0.0003
$\ln C$ does not Granger-cause $\ln P$	3	29	3.71	0.0267
$\ln P$ does not Granger-cause $\ln C$	4	28	14.0	0.0000
$\ln C$ does not Granger-cause $\ln P$	4	28	3.41	0.0290

Table 5: Granger tests for *ex-ante* causality.

B.4 Deriving an $SVAR$ model in logarithmic cost and price differences

From the cointegration and causality results we derive that a relationship between logarithmic cost and price differences is likely to exist. In particular, according to the univariate time series analysis, the differences κ_t of the logarithmic costs and λ_t of the logarithmic prices are assumed to follow an $SVAR(2)$ model of the following form:

$$\begin{pmatrix} 1 & d_{12} \\ d_{21} & 1 \end{pmatrix} \begin{pmatrix} \kappa_t \\ \lambda_t \end{pmatrix} = \begin{pmatrix} a_1 \\ a_2 \end{pmatrix} + \begin{pmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{pmatrix} \begin{pmatrix} \kappa_{t-1} \\ \lambda_{t-1} \end{pmatrix} + \begin{pmatrix} c_{11} & c_{12} \\ c_{21} & c_{22} \end{pmatrix} \begin{pmatrix} \kappa_{t-2} \\ \lambda_{t-2} \end{pmatrix} + \begin{pmatrix} \varepsilon_{\kappa t} \\ \varepsilon_{\lambda t} \end{pmatrix}, \quad (58)$$

[7]The model is $SVAR$ since contemporaneous effects of logarithmic costs and logarithmic prices on each other will be considered *a priori*.

$\widehat{\phi}$	first case	second case	final model
$\widehat{a}_1$	-0.00712 (0.0188)	-0.00712 (0.0188)	0
$\widehat{a}_2$	-0.103^{**} (0.0239)	-0.103^{**} (0.0239)	-0.0807^{**} (0.0176)
$\widehat{b}_{11}$	-0.178 (0.162)	-0.178 (0.162)	0
$\widehat{b}_{12}$	0.396^{**} (0.128)	0.396^{**} (0.128)	0.369^{**} (0.0791)
$\widehat{b}_{21}$	-0.758^{**} (0.206)	-0.758^{**} (0.206)	-0.648^{**} (0.198)
$\widehat{b}_{22}$	-0.547^{**} (0.163)	-0.547^{**} (0.163)	0.672^{**} (0.133)
$\widehat{c}_{11}$	-0.558^{**} (0.193)	-0.558^{**} (0.193)	0.575^{**} (0.125)
$\widehat{c}_{12}$	-0.0118 (0.120)	-0.0118 (0.120)	0
$\widehat{c}_{21}$	-0.319 (0.246)	-0.319 (0.246)	0
$\widehat{c}_{22}$	-0.254 (0.153)	-0.254 (0.153)	-0.360^{*} (0.133)
$\widehat{d}_{12}$	-0.0455 (0.146)	0	0
$\widehat{d}_{21}$	0	-0.0737 (0.236)	0
R^2_κ	0.422	0.422	0.390
R^2_λ	0.596	0.596	0.572
AIC	-149	-149	-140
BIC	-145	-145	-132

Table 6: Estimation of $SVAR(2)$ for differences in logarithmic costs and prices.

where $\varepsilon_{\kappa t}$ and $\varepsilon_{\lambda t}$ are identically and independently distributed ($i.i.d.$) variables with mean 0 and variance-covariance matrix

$$\begin{pmatrix} \sigma^2_\kappa & \sigma_{\kappa\lambda} \\ \sigma_{\kappa\lambda} & \sigma^2_\lambda \end{pmatrix}. \tag{59}$$

It is not possible to fit the model presented by equation (58) directly in STATA.[8] Instead, we analyze to cases. In the first case d_{21} is set equal to 0 and the model is fitted, and in the second case the model is fitted under the condition that d_{12} is equal to 0. We employ the general-to-specific approach, where we introduce more zero constraints when coefficients are not significant. In the first case the following coefficients are consecutively set equal to zero: c_{12}, d_{12}, a_1, b_{11}, and c_{21}. In the second case this sequence is c_{12}, d_{21}, a_1, b_{11}, and c_{21}. We conclude that there are no contemporaneous effects in our final model. In Table 6 the first regressions of each case and the final regression are presented.

Substitution of the estimated parameters in equation (58) leads to

[8]Neither is this possible in EViews nor in SAS.

Null Hypothesis	Wald statistic χ^2_1	Excess Probability
$\ln C$ does not Granger-cause $\ln P$	21.8	0.0000
$\ln P$ does not Granger-cause $\ln C$	10.7	0.0001

Table 7: Granger tests for *ex-post* causality.

$$\begin{pmatrix} \widehat{\kappa}_t \\ \widehat{\lambda}_t \end{pmatrix} = \begin{pmatrix} 0 \\ \underset{(0.0176)}{-0.0807} \end{pmatrix} + \begin{pmatrix} 0 & \underset{(0.0791)}{0.369} \\ \underset{(0.198)}{-0.648} & \underset{(0.133)}{0.672} \end{pmatrix} \begin{pmatrix} \kappa_{t-1} \\ \lambda_{t-1} \end{pmatrix} + \begin{pmatrix} \underset{(0.125)}{0.575} & 0 \\ 0 & \underset{(0.133)}{-0.360} \end{pmatrix} \begin{pmatrix} \kappa_{t-2} \\ \lambda_{t-2} \end{pmatrix}. \tag{60}$$

The variance-covariance matrix of the residuals is given by

$$\begin{pmatrix} \widehat{\sigma}^2_\kappa & \widehat{\sigma}_{\kappa\lambda} \\ \widehat{\sigma}_{\kappa\lambda} & \widehat{\sigma}^2_\lambda \end{pmatrix} = \begin{pmatrix} 0.00334 & 0.000264 \\ 0.000264 & 0.00543 \end{pmatrix}. \tag{61}$$

B.5 *Ex-post* causality

The VAR model can be used to test the null whether lagged values of a variable, say x, have explanatory power in a regression of a variable y on lagged values of y and x. Testing for such Granger-causality can also be executed through a Wald test, which boils down to test zero constraints for the coefficients of an estimated $VAR(p)$ model.

In general, we consider testing $\mathbf{C}\boldsymbol{\beta} = \mathbf{c}$ against $\mathbf{C}\boldsymbol{\beta} \neq \mathbf{c}$, where $\mathbf{C}$ is an $(m \times (k^2p + q))$ matrix of rank m, k is the dimension of the $VAR(p)$ process (k is the number of equations in the VAR model; 2 in our case), and $\mathbf{c}$ is an m vector (also containing zero restrictions in our case). Assuming that $\sqrt{T}\left(\widehat{\boldsymbol{\beta}} - \boldsymbol{\beta}\right) \xrightarrow{d} N(\mathbf{0}, \mathbf{V})$, with $\mathbf{V}$ the asymptotic variance-covariance matrix, we get (see e.g. Plasmans (2006, p. 39))

$$\sqrt{T}\left(\mathbf{C}\widehat{\boldsymbol{\beta}} - \mathbf{C}\boldsymbol{\beta}\right) \xrightarrow{d} N(\mathbf{0}, \mathbf{CVC}'), \tag{62}$$

and hence

$$T\left(\mathbf{C}\widehat{\boldsymbol{\beta}} - \mathbf{c}\right)' \left[\mathbf{CVC}'\right]^{-1} \left(\mathbf{C}\widehat{\boldsymbol{\beta}} - \mathbf{c}\right) \xrightarrow{d} \chi^2_m, \tag{63}$$

which involves the Wald test statistic W (the expression on the left hand side of (63) with an estimate of $\mathbf{V}$) having a limiting chi-squared distribution with m degrees of freedom. Usually, the null hypothesis is that a certain subvector of $\boldsymbol{\beta}$, say $\boldsymbol{\beta}_0$, equals zero so that the Wald test statistic in (63) becomes $W_0 = \mathbf{c}_0'\widehat{\mathbf{V}}_0^{-1}\mathbf{c}_0$, where $\widehat{\mathbf{V}}_0$ (c_0) denotes the corresponding submatrix (subvector) of $\widehat{\mathbf{V}}$ (c).

Table 7 presents the STATA results of this Wald (*ex-post* causality) test applied to the estimated $VAR(2)$ model in (60), where m is the number of *ex-post* restrictions that can be imposed on each equation of (60), i.e. not considering the coefficients already set to zero *ex-ante*. Hence, we have $m = 1$ *ex-post* zero constraint to be tested in each equation of (60).

We conclude that there is a clear *ex-post* causality between logarithmic costs and logarithmic prices in both directions as both null hypotheses of no-causality are strongly rejected.

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