Aalto University
School of Economics

Estimating the Demand and Market Power of a Firm in Sawn Wood Markets

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Master's thesis

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Case: UPM-Kymmene

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1. examiner 2.examiner

Abstract

AALTO UNIVERSITY SCHOOL OF ECONOMICS 5.5.2011
Economics department

Otto Olsson

Estimating the Demand and Market Power of a Firm in Sawn Wood Markets

The high concentration levels and the static structure of the sawn wood markets in Finland give reason to believe that the firms in the market have market power. The aim of this study is to investigate whether UPM-Kymmene has market power in Finnish sawn wood markets by analyzing the elasticity of its residual demand. Based on this analysis UPM-Kymmene will get better information on the environment it operates in and can improve its sales strategies.

The study is based on empirical research using time series data from UPM-Kymmene's sales databases and also from other public sources. Based on the UPM-Kymmene's sales volumes, four separate product groups are chosen for the analysis. The product groups include one center good and one board product for both redwood and whitewood.

In the empirical part, the study follows the residual demand literature starting from Baker and Bresnahan (1988) and uses two stage least squares method to take into account the simultaneous relation between quantity sold and price.

The current literature has neglected nonstationarity issues in its analyses. This study expands on the current literature and takes into account the nonstationarity inherent in economic time series by estimating also a vector error correction model using Johansen's (1988) method.

Based on the results, UPM-Kymmene does not have market power in Finnish sawn wood markets and the prices are determined by industry-wide cost and demand factors. Thus UPM-Kymmene should not try to influence the prices by cutting its production.

Keywords: residual demand, elasticity of demand, market power, two stage least squares, Johansen's method.

Tiivistelmä

AALTO-YLIOPISTON KAUPPAKORKEAKOULU 5.5.2011
Kansantaloustieteen laitos, pro gradu -tutkielma

Otto Olsson

Sahatavaramarkkinoilla toimivan yrityksen kysynnän ja markkinavoiman estimointi

Suomen sahatavaramarkkinoiden korkea keskittyneisyysaste ja staattinen markkinarakenne antavat syyn epäillä siellä toimivilla yrityksillä olevan markkinavoimaa. Tämä tutkielma pyrkii selvittämään, onko UPM-Kymmenellä markkinavoimaa Suomen sahatavaramarkkinoilla. Analyysin perusteella UPM-Kymmene saa paremman käsityksen toimintaympäristöstään ja voi mahdollisesti parantaa myyntistrategiaansa.

Tutkielma pohjautuu empiiriseen analyysiin UPM-Kymmenen myyntitietokantojen ja muiden julkisten lähteiden dataa käyttäen. Analyysiin on valittu neljä UPM-Kymmenen myynnin volyymien perusteella merkittävää tuoteryhmää. Tuoteryhminä ovat yksi sydänpuu- ja yksi lautatuoteryhmä sekä mänty- että kuusipuulajeista.

Tutkielman empiirinen osuus seuraa tarkasti jäännöskysyntäkirjallisuutta, jonka pohjan loi Baker ja Bresnahan (1988), ja käyttää two stage least squares –menetelmää, joka huomioi hinnan ja myyntimäärän välisen simultaanisuuden.

Nykyinen jäännöskysyntäkirjallisuus jättää aikasarjojen epästationäärisyyden huomiotta. Tämä tutkielma laajentaa nykyistä kirjallisuutta ja huomioi taloudellisille aikasarjoille ominaisen epästationäärisyyden estimoimalla kysyntää myös vektorivirheenkorjausmallilla Johansenin (1988) menetelmällä.

Tulosten perusteella UPM-Kymmenellä ei ole markkinavoimaa Suomen sahatavaramarkkinoilla. Hinnat määräytyvät koko toimialaa koskevien kustannus- ja kysyntätekijöiden perusteella. Täten UPM-Kymmenen ei tule pyrkiä vaikuttamaan hintoihin tuotantopäätöksillään.

Avainsanat: jäännöskysyntä, kysynnän hintajousto, markkinavoima, two stage least squares, Johansenin menetelmä.

Contents

1. Introduction

Residual demand is the demand facing a single firm. A residual demand curve describes how price and the firm's own quantity sold interact, taking into account competitors' strategic responses. Landes and Posner (1981) decompose the elasticity of residual demand into three components: the elasticity of demand of the whole market, the elasticity of supply of the competitive fringe and the market share of the firm in interest. All these components are important in determining the residual demand of a single firm.

The link between the market power of a firm and its elasticity of demand has been established already in Lerner index (Lerner, 1934). The Lerner index is a generally accepted measure of market power. It describes a firm's market power as the power to price with a markup over marginal costs. Still, using the Lerner index to measure market power is hard because of the abstract nature of marginal costs; an increase in costs resulting from a marginal increase in quantity produced is difficult to estimate especially with only public data available.

The Lerner index can also be expressed using the elasticity of residual demand. Estimating this elasticity from a system of Marshallian demand equations requires taking into account all the relevant substitutes and competitors. Neglecting substitutes or defining the markets too broadly can result in an over- or underestimation of the true market power. The main contribution of Baker and Bresnahan (1988) to the market power literature is in developing a way to estimate the elasticity of the demand curve facing a single firm, i.e. the residual demand curve, without the need to separately and explicitly take into account all the substitutes and reactions of competitors.

Residual demand analysis is usually used in the context of antitrust related cases. Using statistical estimations has been a growing trend in antitrust courts in the United States. This is due to two main reasons. Firstly, computers and their computing power has increased tremendously making it easy to apply methods that in the past were time consuming and hard to carry out. Secondly, the antitrust courts in the US have had a growing interest in statistical evidence of the effects of mergers and abuse of monopoly power. (Baker and Rubinfeld, 1999.)

The statistical tools available to antitrust authorities focus mainly on identifying the existence of market power. As the elasticity of residual demand is closely related to the Lerner index, it is one of the few tools that antitrust courts have to measure the actual size of market power. This makes it a useful tool in antitrust cases and it is why it has been widely applied. The Finnish competition authorities have also included residual demand analysis in their framework for competition analysis (Björkroth et al. 2006a).

Although residual demand analysis is usually used in the context of antitrust related cases, it can also be a useful tool for a firm that wants to gain understanding of its business environment, markets and the nature of its demand. For example, a firm that knows the elasticity of the demand curve it faces can use this information to improve its sales planning and forecasting to determine how an increase in sales quantities affects its price. Econometric estimations also provide more general information on how costs and macroeconomic variables will influence the demand. Firms often have tacit knowledge on these issues, but statistical analysis can support this knowledge or, in some cases, correct common misconceptions within the firm.

In this paper residual demand analysis is used to investigate the demand and market power of a case company, UPM-Kymmene, (from hereon UPM) which operates in the forest industry and is a large multinational forest integrate. It produces traditional forest products such as pulp, paper and sawn wood and, in addition, many other products that use raw materials extracted from forests, such as biofuels.

This study focuses on coniferous sawn wood markets in Finland. The sawn wood industry has a high level of product differentiation. The products are differentiated based on, for example, wood types, the quality of raw material, different moisture levels and dimensions of the product. In addition, product differentiation is done by further processing the sawn wood.

Sawn wood markets are greatly influenced by the raw material markets. Raw material for Finnish sawn wood producers comes mainly from domestic markets. The defining feature of these markets is that the Finnish forest reserves are mostly in the hands of small private owners who are generally not professionals in forestry. The demand for sawn wood comes mainly from construction industry and industries related to construction, such as joinery. As construction is generally known as an industry sensitive to economic fluctuations, these fluctuations are also transferred to the sawn wood industry.

In Finland, the sawn wood market is dominated by three large players: Metsäliitto, Stora Enso and UPM. Due to the high concentration in the market, UPM has a large market share and one might expect it to also have a large market power. Using the elasticity of residual demand, this study aims at measuring UPM's market power in four different submarkets for four different product groups.

The main research questions this paper tries to answer are:

- Does UPM have market power in the Finnish sawn wood markets?
- How can UPM take the potential market power into account in its sales planning?

This study uses both public and private data in its analyses. This is a major advantage to some of the earlier literature that has had to rely on public data only. The observation period used in this study is from January 2004 to December 2010. The data is monthly and there are 84 observations included in the estimations. Like previous residual demand literature, starting from Baker and Bresnahan (1988), this study uses simultaneous equations methods (two stage least squares or 2SLS) to estimate the elasticity of residual demand.

According to Froeb and Werden (1999) the current residual demand literature has neglected nonstationarity issues and dynamic features of the time series in its econometric analyses. This may have led to spurious regressions in 2SLS regressions and can be considered a major flaw in the residual demand literature. This study expands the current literature by analyzing residual demand with Johansen's (1988) method. The vector error correction model used in these estimations accounts for both nonstationarity issues and dynamics and allows us to test the robustness of 2SLS estimation results.

The estimations done show that the prices are not significantly affected by UPM's quantity sold and the residual demand is perfectly elastic. Thus, the results of this study are clear regardless of the estimation method: UPM does not have market power in Finnish sawn wood markets. The prices of sawn wood seem to be determined solely by industry-wide cost and demand factors.

In part two of this study we shortly describe the main characteristics of the Finnish sawn wood markets. Part three defines residual demand more formally and derives the model that is estimated later in the empirical part. Part four presents the main empirical methods used in this study and part five goes through some of the residual demand literature to see what has been taken into account in the previous works and what has been neglected. In parts six and seven present the data and the results. Part eight concludes and discusses the results.

2. Finnish Sawn Wood Industry

In this part, we will present some of the defining features of Finnish sawn wood industry. The most influential features of the industry are the raw material market, the role of sawn wood production as subordinate to paper and pulp production and the nature of demand for sawn wood. This part also presents some of the earlier literature regarding the industry and presents an approach to analyzing its demand.

2.1. Trends in Sawn Wood Production

The forest industry has historically been an important industry for the Finnish economy. However, since the seventies the share of labor in sawn wood production compared with the whole labor force in Finland has had a slight decreasing trend. As can be seen in Figure 1, the share of workers in production of sawn wood and wood products compared with all the workers in industrial production fell from 8.5% in 1975 to 6.5% in 2009 and compared with the whole economy, the share of workers in production of sawn wood and wood products was under 1% in 2009 (www.stat.fi, 10.08.2010).

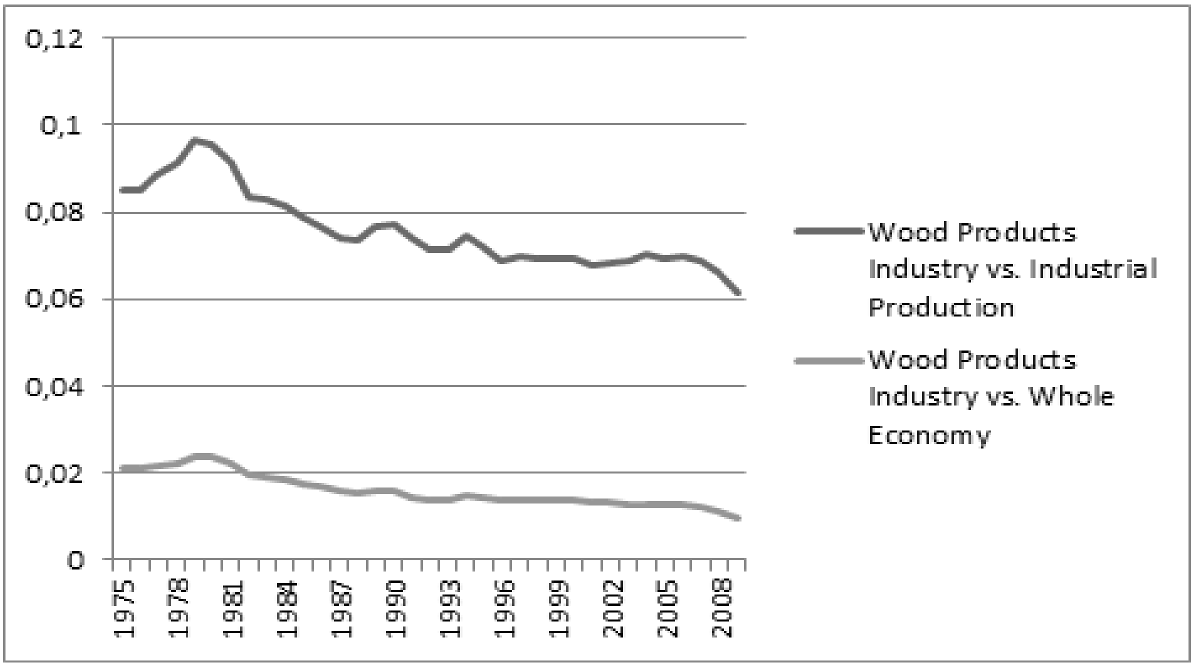

Figure 1. The amount of labor in Finland in wood products industry compared to the amount of labor in industrial production and the whole economy. (Source for data: www.stat.fi, 10.08.2010)..

Although the amount of labor in sawn wood production has been decreasing, the production levels of Finnish coniferous sawn wood grew steadily until the year 2004. The rising levels of production and decreasing share of labor are a sign of more concentrated production. This trend of concentration of production into bigger units has been seen for a long time also in central Europe (Nilsson, 2001). Since 2004 the production has been decreasing partly due to the tougher competition from Swedish producers (see Figure 2.)

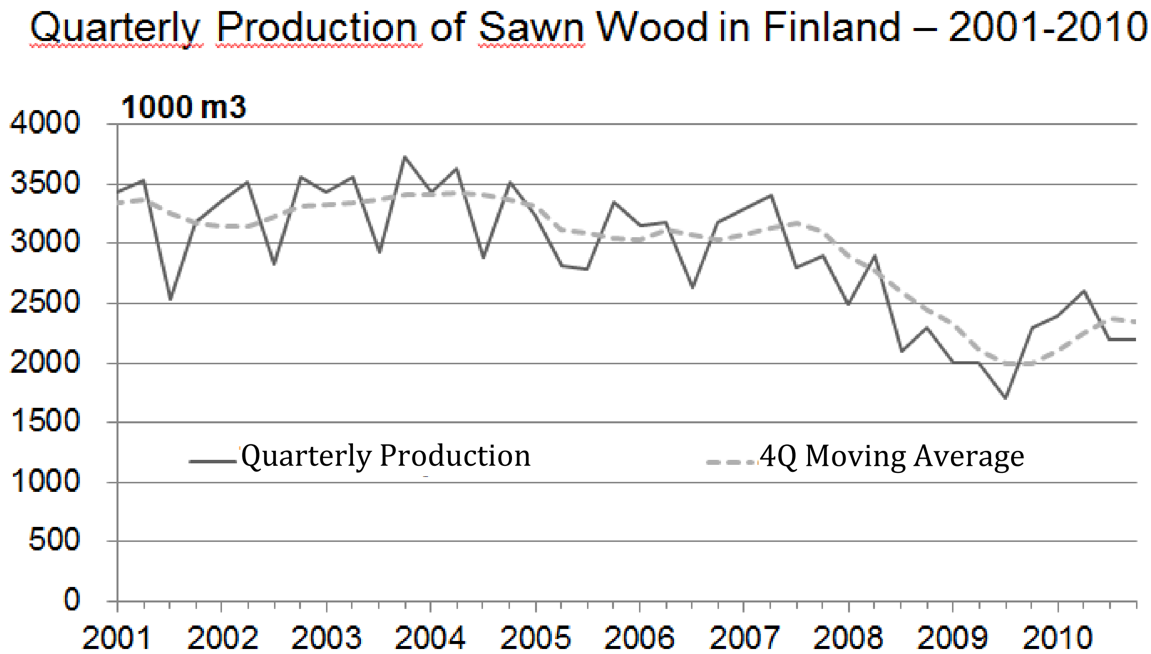

Figure 2. The quarterly production of sawn wood in Finland. (Source: Finnish Forest Industries, 20.4.2011)

When studying the sawn wood industry, it is important to understand that sawn wood is often produced as a part of a much bigger industry, the whole forest industry. The Finnish forest sector is dominated by three large players – Stora Enso, Metsäliitto and UPM that produce all the main forest products – paper, pulp and sawnwood.

The incentives for the integrated production of paper, pulp and sawn wood can be many. When the forest companies buy their raw material, they have to buy it as a bundle of all the trees in a specific area of the forest. Unbundling this package of forest would result in high transaction costs so a company that can use the whole bundle can operate with lower costs. The role of sawn wood production in forest integrates is to use the most expensive part of this bundle, the sawlog. This material is too expensive to be used in pulp and paper production or as energy.

Generally in large multinational forest companies, sawn wood production is subordinate to pulp and paper production. One of the main functions of sawmilling in this setup is producing high-quality wood chips for pulp and paper mills (Kallio, 2001). Kallio (2001) proposes that because of its role in producing wood chips as a by-product, there is even overproduction in sawmilling. This means that sawmills could be run with a loss to enable the production of pulp and paper.

2.2. Raw Materials Market

The costs and availability of raw material are some of the most defining factors of sawn wood production. The main materials for sawn wood products are coniferous, redwood or whitewood logs and the stumpage prices for these wood types drive the prices for sawn wood products. Prices for coniferous logs are generally more volatile than those for fiberwood (see Figure 3). Fiberwood, regardless of the wood type, is cheaper and as its supply is larger, increased demand does not result in large peaks in its prices.

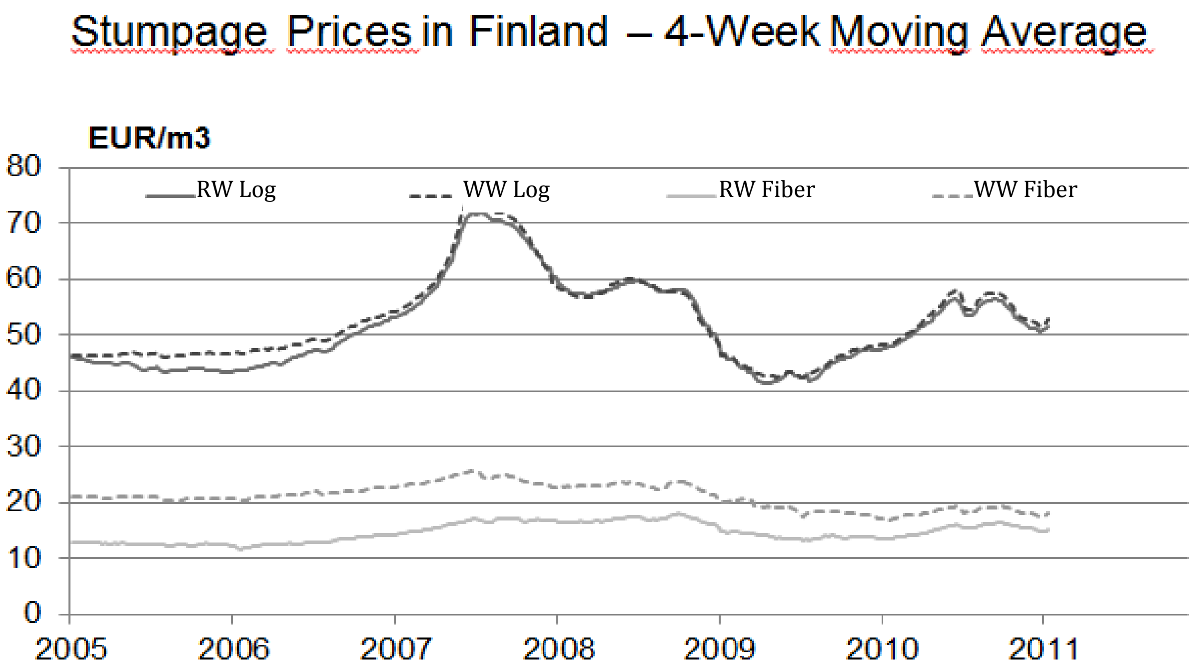

Figure 3. The development of stumpage prices in Finland between 2005 and 2011. The two

highest lines represent redwood and whitewood log stumpage prices, and the lowest lines represent the prices for fiberwood. (Source: Finnish Forest Industries)

As only 14% of the raw wood used by the Finnish forest cluster is imported (Finnish Forest Industries) the relevant market for raw material for Finnish sawn wood industry is the Finnish raw wood market. As can be seen in Figure 4, the reserves for Finnish coniferous raw timber have been increasing steadily since the Second World War increasing the supply of raw material.

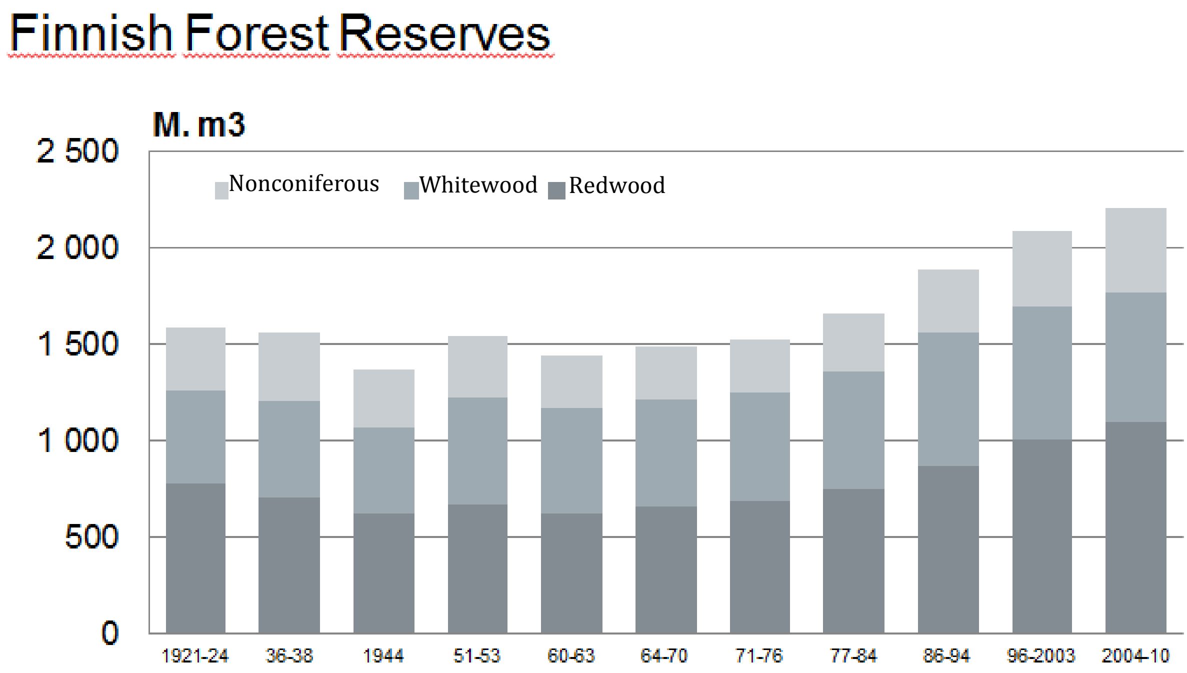

Figure 4. Finnish forest reserves measured in millions of cubic meters. The lowest part of the histogram represents the reserves of redwood, the middle part the reserves of whitewood and the top part the reserves of birch. For sawn wood industry and this study, the most important wood types are whitewood and redwood, and as can be seen from the picture, the reserves have experienced steady growth since WWII. (Source: Finnish Forest Industries.)

The division of forest ownership in Finland affects the availability and price setting in the raw material markets. Most of the supply of raw timber comes from privately owned forests and the ownership is widely scattered. As can be seen in Figure 5., the Finnish forests are mostly in the hands of private owners. Finland has over 900 000 forest owners (Finnish Forest Industries) making the seller side of raw wood highly dispersed.

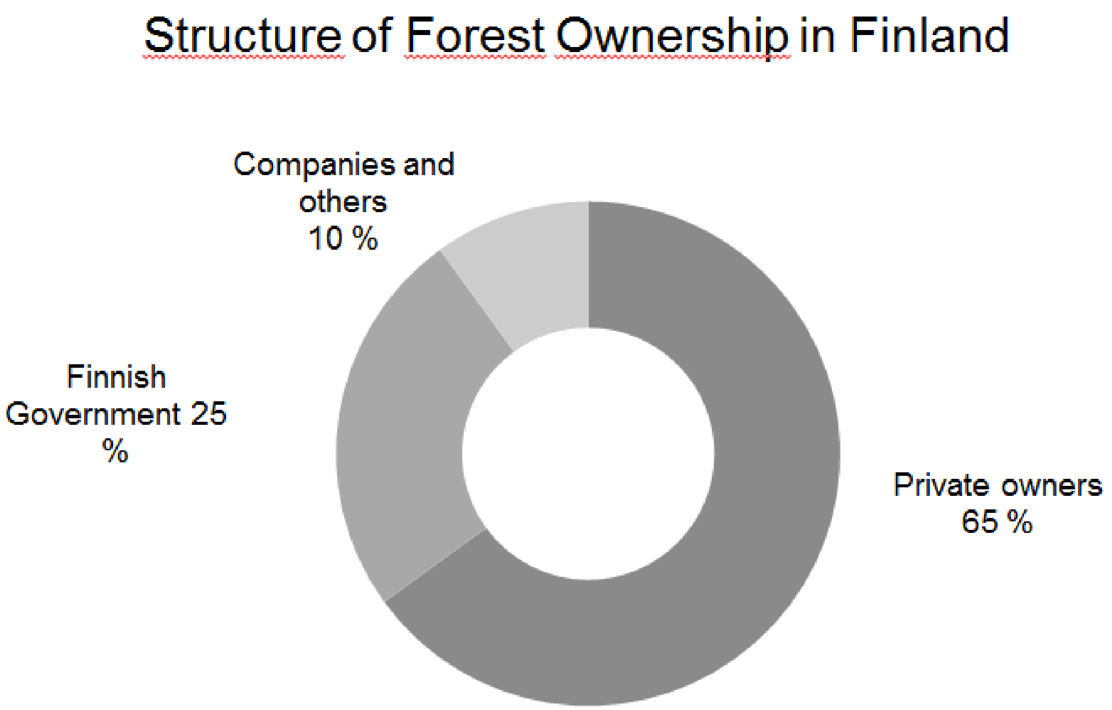

Figure 5. Structure of ownership of Finnish forest reserves. 65% of Finnish are owned by private owners, 25% of the forests are state owned and the forest companies, municipalities and other agents own 10% of the forests. (Source: Finnish Forest Industries.)

Because of their small size, the forest owners cannot have a lot of market power in the raw wood market - especially when the buyer side in roundwood market is highly concentrated. The three largest buyers, Metsäliitto Osuuskunta, Stora Enso Metsä and UPM Metsä buy 82% of all the raw wood (Björkroth et al., 2006b). Furthermore, the possibility for these large companies to import wood from neighboring countries, even if the amount of imports is only 14%, should increase their buyer power and help drive the price of raw wood down.

Björkroth et al. (2006b) find statistically significant differences between raw wood prices in different areas of Finland indicating that the markets for raw wood are, at least partly, geographically separated. Hänninen et al. (2006) find significantly different elasticities of demand for raw wood in different parts of the country supporting the idea of separate markets inside the country. According to Björkroth et al. (2006b) findings, the prices in Finnish timber markets are low when compared with the Swedish markets and the prices experience small variances.

The high concentration, low prices, small variances in prices and differences in prices inside the country all give rise to suspect collusion in the market, and indeed, in 2009 a buyer side cartel between the three large players in the Finnish raw wood market was revealed to have been operating between 1997 and 2004. However, Kallio (2002) claims that in normal economic times the forest companies do not have a reason to limit their demand of raw wood to cut prices. Thus a cartel, which only later was found to actually exist in the market, would not cause major welfare losses. This is largely because of the supply elasticities that limit the companies' ability to use oligopsony power. The short-run elasticities of supply for raw wood, estimated for different parts of Finland were between 0.86–3.54 making the supply elastic in most parts of the country but in the long-run, supplies were found to be inelastic (Hänninen et al., 2006).

Even without a functioning cartel, one would think that the increasing forest reserves and low concentration levels of forest ownership and the large size of the buyers would force the prices for raw wood down. Still, a constant complaint of the Finnish forest cluster is the insufficient supply and high prices of domestic raw material. The forest industry's typical argument is that as the usual forest owner is not a professional in forestry and his or her livelihood is not dependent on selling the wood, the owners are able to wait out periods of low prices without significant waiting costs. At the same time, the industry whose operations are completely dependent on the availability of raw material and that has significant waiting costs has to offer high prices to induce selling. This, according to the usual argument of forest industry, can drive up the stumpage prices and cause high costs for the whole industry. Basically, the forest industry's argument goes along the lines of Hänninen et al. (2006) results that the elasticity of supply of raw wood prohibits the use of oligopsony power.

2.3. Demand for Sawn Wood

The sawn wood market does not have a single market place where a spot price would be set. Instead, the sales prices and quantities are negotiated directly with the customers. This means that negotiating power and long relationships with customers are likely to affect the prices.

For our case company, UPM, there are two easily identifiable customer groups in the market: industrial buyers and distributors. Industrial buyers that buy goods for their own production value a stable supply of goods even more than a low price and they are often described as less sensitive to prices. Distributors, on the other hand are described as more speculative buyers and they are likely to be more sensitive to prices.

Based on the standard deviations on prices and quantities of selected products presented in Table 1, there is no reason to believe that the demand for one group is more fluctuating than for the other, but of course this does not mean that the two groups could not have different elasticities of demand.

Table 1. Variances of prices and quantities for industrial end-users and distributors for the different product groups analyzed in this study.

Type A	Product 1				Product 3			
	Industrial		Distribution		Industrial		Distribution	
	Price (€/m3)	Quantity (m3)	Price (€/m3)	Quantity (m3)	Price (€/m3)	Quantity (m3)	Price (€/m3)	Quantity (m3)
St.Dev.	13,4 %	77,4 %	14,9 %	57,4 %	18,1 %	40,2 %	19,2 %	59,9 %
Type B	**Product 2**				**Product 4**			
	Industrial		Distribution		Industrial		Distribution	
	Price (€/m3)	Quantity (m3)	Price (€/m3)	Quantity (m3)	Price (€/m3)	Quantity (m3)	Price (€/m3)	Quantity (m3)
St.Dev.	14,1 %	80,6 %	13,3 %	66,6 %	19,3 %	38,5 %	21,0 %	55,8 %

One reason why setting a spot price for sawn wood products is difficult is that the industry has a high level of product differentiation. First of all, the coniferous sawn wood products are divided between redwood and whitewood products based on the type of wood they are made of. Another significant factor in determining the value of the product is the part of the tree used in production. The terms used are boards and center-good products, where boards are produced from cheaper parts of the tree. Different moisture levels, the dimensions of the end-product and the overall quality of the raw material used bring other means of differentiating the products.

In this study, four product groups are chosen for analysis based on the size of sales. The chosen product groups are the same as in table 1: products 1 and 2 represent center-good products of both wood types and products 3 and 4 are boards of both wood types. [1]

On the demand side, it is important to recognize that the demand for sawn wood is in essence derived demand. In other words, sawn wood is always used for producing something else. The demand for sawn wood ultimately depends on the demand for the goods that sawn wood is used to produce. Thus, the demand for sawn wood is a function of variation and activity levels in different sectors that use sawn wood and of the intensity of utilization of sawn wood.

Usually, sawn wood is used as a material in construction, furniture manufacturing or in production of joinery products such as windows and doors. The most significant and widely acknowledged demand driver for sawn wood products in any market is the construction industry (Finnish Forest Industry). As can be seen in Figure 6, sawn wood demand closely follows the number of new construction projects. Thus, factors that affect the number of new construction projects are likely to affect the demand of sawn wood as well. These factors include e.g. the general economic activity and, especially in the long-run, demographic factors such as the birthrate and flows of migration. Construction is generally considered very sensitive to economic cycles and this sensitivity is carried on to the sawn wood industry.

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[1] Due to privacy reasons, closer specification of the products studied in the empirical part cannot be given and instead of different woodtypes and product specifications the empirical part speaks only of woodtypes A and B and products 1, 2, 3 and 4.

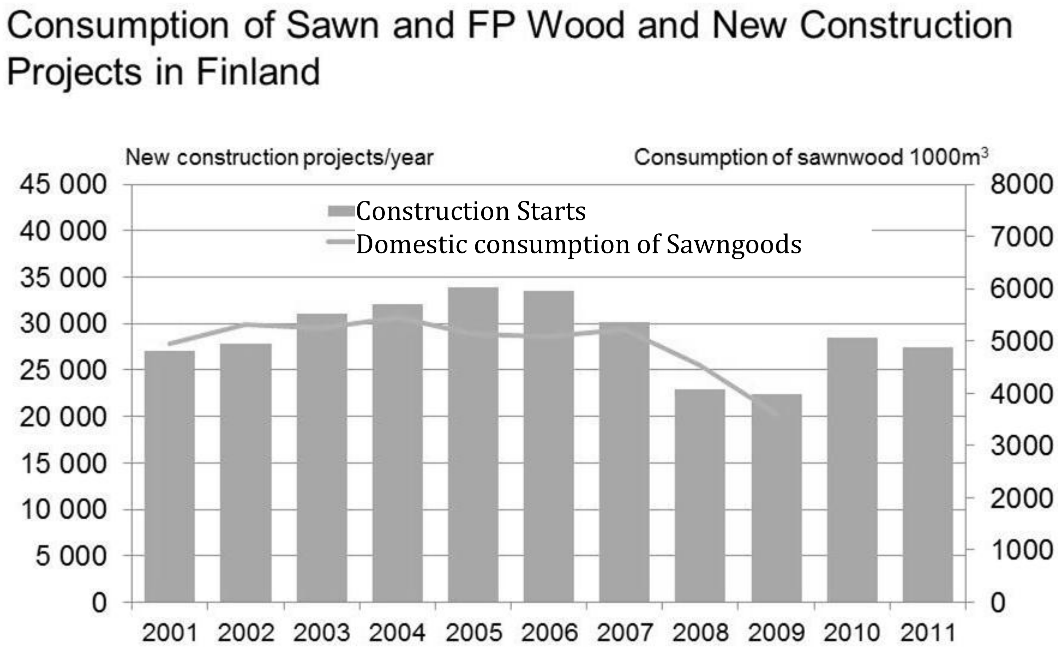

Figure 6. Consumption of sawn wood and further processed wood and the number of new housing projects (Source: Finnish Forest Industries). The grey pillars depict the amount of new construction projects (left scale) and the green line the consumption of sawn wood in thousands of cubic meters. The demand for sawn wood and further processed wood products follows closely the new housing starts.

Although Finland is the single biggest market for coniferous sawn wood products for our case company UPM, exports play a major role for all the large multinationals Stora Enso, UPM and Metsäliitto. In 2009, for example, approximately half of the Finnish sawn wood and plywood production was exported to outside the Eurozone. The large share of exports makes exchange rates an important driver of both demand and costs.

The effect of exchange rates was clearly seen during almost the whole previous decade, as Swedish producers experienced a significant competitive advantage due to developments in EUR/SEK exchange rate. Another factor that decreased the competitiveness of Finnish sawn wood products during that time was the 2004 storms in Sweden that cut down large areas of forests, increased the availability of raw wood and decreased the costs for Swedish producers. This shows up especially when looking at the production and exports of redwood and whitewood separately as is done in

Figure 7. While the exports of whitewood have experienced a severe drop since 2004, exports of redwood remained remarkably steady (Hänninen & Viitanen, 2010).

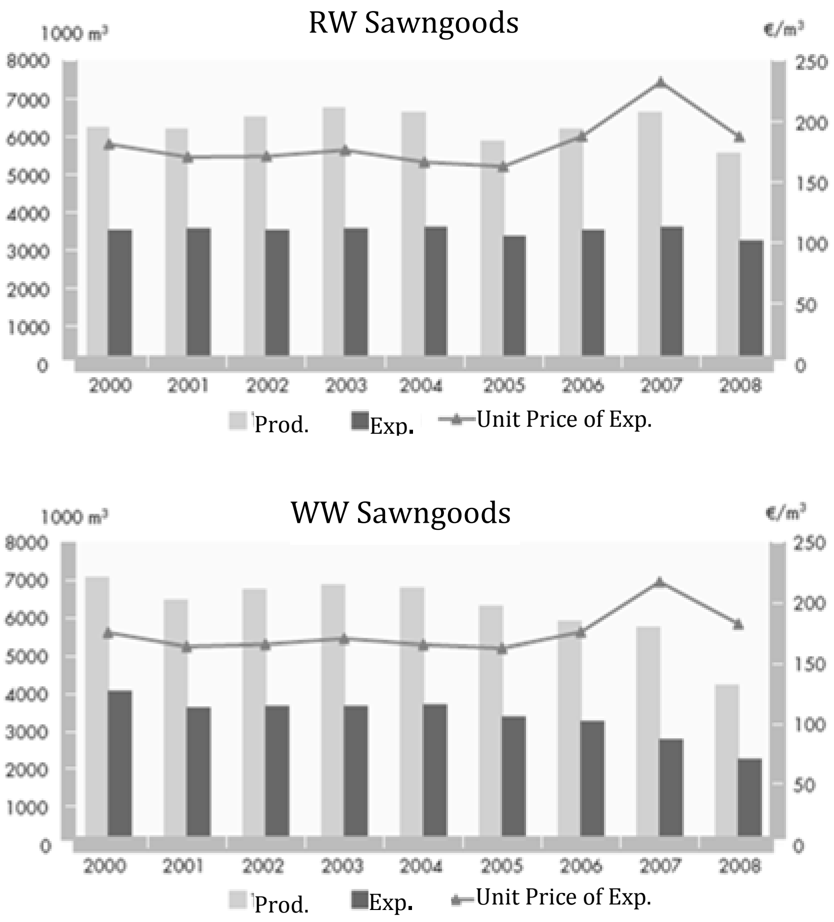

Figure 7. Production, exports (m3) (left scale) and export's unit prices (€/m3) (right scale) for redwood and whitewood. (Source: Metsätieteen aikakauskirja 2/2010). Exports and also the production of whitewood decreased substantially after 2004.

Figure 7 also shows that from 2005 to 2007 the unit price of both redwood and whitewood increased as the production could not meet the increase in demand and, in addition, the costs rose rapidly. The financial crisis led to a decrease in exports in 2008 due to a slowdown in global construction. (Hänninen & Viitanen, 2010.)

2.4. Modeling the Derived Demand in Sawn Wood Markets

Economic analyses of sawn wood products are not easy to find and it seems that this market is not analyzed as often as other forest product markets such as pulp and paper, or the markets for raw wood. There can be many reasons for this, for example the industry's subordinate status or the high number of different products that the industry produces that complicates the analysis.

Baudin (2003) summarizes several attempts to model the market so as to take into account the nature of the demand as derived from the demand for other markets. The models used are constructed from end-use perspective so that they first look at the developments of different sectors that use sawn wood and then combine this information to analyze the development of sawn wood markets. This kind of analysis provides a better understanding how, for example, the substitution between sawn wood and other products work. For example, for the UK market Baudin (1992 and 1993) tried to estimate how the number of new housing projects would develop and then combine this information with the information on how much sawn wood is used per new house. Similar analysis was done for 19 different sectors for the UK (Baudin, 1992 and 1993).

In studies summarized by Baudin (2003), for each sector *m* producing a single product, the production function is of the following form:

$$y_{mt} = y_{mt}(v_{mt}, z_{mt}, t)$$

where y_{mt} is the output of sector *m* during time t, v_{mt} is sawn wood used as input in production, z_{mt} is a vector of other production input in sector *m* and *t* is an index of time representing technological change, t = 1, ..., T.

Minimizing costs subject to the production function above and using Shepard's lemma, the demand for sawn wood at time *t* can be expressed as

$$v_{mt} = v_{mt}(y_{mt},\ p_{0t},\ p_{1t},\ p_{2t}, \dots, p_{nt})$$

where p_{0t} is the unit price of sawn wood during period *t* and p_{it} are the unit prices of other inputs in sector *i* at time t when *i = 1, ..., k* and the unit prices of other goods during time *t* when *i = k+1, ..., n*.

Now, the total production of sawn wood is determined by consumer demand. For consumer *j*, the demand for product *m* is a function of prices for all products, both sawn wood products and other goods and the income consumer *j* receives, I_j.

$$y_{mjt} = y_{mjt}(p_{0t}, p_{1t}, p_{2t}, \dots, p_{nt}, I_{jt})$$

and for the whole sector m, taking into account time as consumers do not react to changes immediately, the aggregated demand is then

$$y_{mt} = y_{mt}(p_{0t}, p_{1t}, p_{2t}, \dots, p_{nt}, Y_t),$$

where Y_t is GDP at time t.

These sector models are then estimated as Seemingly Unrelated Regression Equations (SURE) (Zellner and Theil, 1962) to capture the underlying similarities between the models - for example general trends, business cycles and the effects of construction industry. These similarities between the models show up in the covariances of errors between the different equations. SURE-method captures the covariances and can offer more precise estimates.[2] The sector models are estimated in log-linear form so that the coefficients can be interpreted as elasticities.

Baudins end-use approach finds the elasticities of substitution between different products and provides closer information on consumers' preferences. Compared to Baudin's analyses, residual demand analysis that we will focus on in the next part loses some of this information of the buyers preferences, but on the other hand, it provides a view of the strategic response of buyers and competitors to firm's sales decisions.

[2] For further discussion on SURE-method, refer to e.g. Greene (2000)

3. Residual Demand Analysis

Residual demand analysis has been mostly used by competition authorities in antitrust cases to analyze, for example, mergers or potential collusion in oligopoly situations. Also the Finnish competition authorities use residual demand analysis as part of their framework for competition analysis (Björkroth et al. 2006a). Although residual demand analysis is typically used to detect market power by outside authorities, it also provides valuable information for the firms themselves. The aim of this study is to analyze the residual demand for UPM to provide more information on the business environment they operate in and to improve their sales planning processes.

In this chapter, we will first define residual demand more formally and then present the theoretical background which residual demand analysis rests on. After this we can derive a residual demand model that is estimated by econometric means in the later parts of this paper.

3.1. Theoretical Background and Definition

Residual demand is defined as that part of the market demand that competitors do not satisfy. In essence, it is the demand that a firm faces taking into account the supply responses of other firms in the market. More formally residual demand can be expressed as a function of price level p. Defining S(p) as the supply of other firms in the market and D(p) as the market demand, residual demand for firm i, $R_i(p_i)$, can be expressed as

$$R_i(p_i) = D(p_i) - S(p_i)$$

Residual demand is thus the horizontal distance between supply of other firms and the market demand in (P,Q) space. This can be seen in Figure 8.

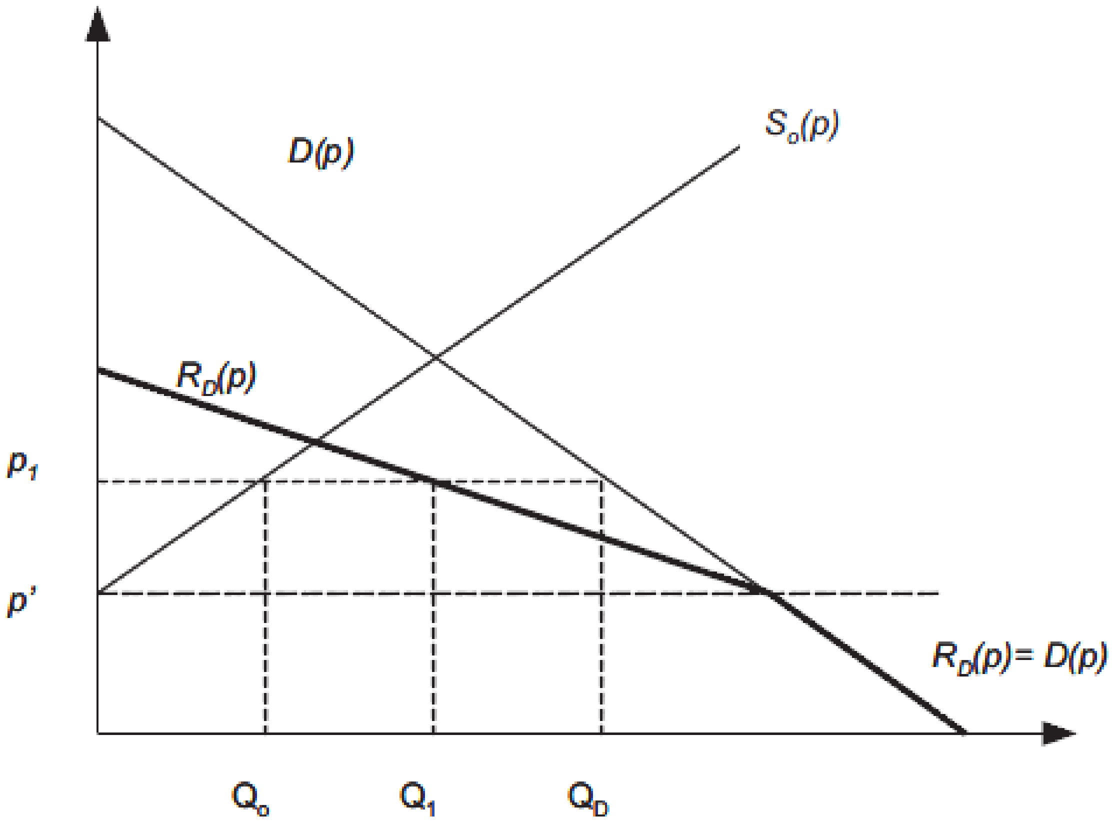

Figure 8. Residual demand in (P,Q) space. Residual demand at price p is the horizontal distance between supply of other firms in the market, *$S_0(p)$* and the market demand *D(p)*. This is the part of the demand that is not satisfied at price *p*, i.e. the demand that the firm in interest can satisfy. (Edited from Björkroth et al. 2006a picture.)

For a monopolist, the supply curve $S(p_i)$ in Figure 8 is naturally non-existent as there are no other suppliers and its residual demand equals the market demand. For a firm with no market power, the residual demand curve is flat, as the firm is a price taker - any decrease in firm's output is fully compensated by an increase in the output of other firms. For an oligopolist with some market power, the residual demand curve is somewhere in between these two extremes.

Residual demand analysis rests on the theoretical decomposition of Landes and Posner (1981) of the relation between a dominant firm's market power and its own market share adjusted with the market demand elasticity and the fringe supply elasticity. Landes and Posner's (1981) decomposition, on the other hand, is closely related to

Lerner index (Lerner, 1934), which measures the firm's market power as a markup over marginal costs. The Lerner index can be written as follows:

$$L_i = \frac{P_i - MC_i}{P_i},$$

where L_i is the Lerner index for firm i, and P_i and MC_i are the price and marginal costs for firm i. The equation above can also be expressed in terms of elasticity of demand the firm faces. To see more clearly why markup and firm's elasticity of demand depend on each other, let's look more closely at the Lerner-index (Lerner, 1934). Firm i is maximizing its profit and thus the profit maximizing condition must apply:

$$MR_i = MC_i.$$

As MR_i is the first derivative of total revenue, we can write for a dominant firm

$$MR_i = P_i + Q_i \frac{dP_i}{dQ_i},$$

where Q_i is the quantity sold for firm i. Noting that $MR_i = MC_i$ and substituting MC_i in Lerner index with the above equation for MR_i, we get

$$L_i = \frac{P_i - MR_i}{P_i}$$

$$= \frac{P_i \; - \; P_i \; - \; Q_i \; {}^{dP_i}/_{dQ_i}}{P_i}$$

$$= -\frac{Q_i}{P_i}\frac{dP_i}{dQ_i}$$

$$= -{}^{1}/_{e_{d1}}$$

$$\rightarrow \; L = -{}^{1}/_{e_{d1}},$$

where e_{di} is the firm's elasticity of demand.

If the residual demand is completely elastic, i.e. elasticity is minus infinity, the firm has no possibility to overcharge and $P_i = MC_i$. We can conclude that the firm is a price taker and increasing the price will cause the quantity sold to collapse. On the other hand, a firm with market power will not produce in the inelastic part of the residual demand curve, as it is profitable to cut production as long as the residual demand is elastic, so we can conclude that the range for firm's elasticity of demand ranges from -1 to minus infinity.

It is important to understand that the relevant elasticity here is the elasticity of demand that the firm faces, not the elasticity of market demand. To show more clearly the components that affect the firm's elasticity of demand, Landes and Posner (1981) derive the elasticity of residual demand for firm i. Starting from the definition of residual demand, the quantity demanded for firm i Q_i is the difference between total quantity demanded Q and the quantity supplied by other firms Q_{-i}.

$$Q_i = Q - Q_{-i}$$

Differentiating this with respect to price and multiplying both sides with$(-P/Q_i)$ yields

$$-\frac{P}{Q_i}\frac{dQ_i}{dP} = -\frac{P}{Q_i}\frac{dQ}{dP} + \frac{P}{Q_i}\frac{dQ_{-i}}{dP}$$

Denoting market share for firm i with S, the quantity demanded for firm i can be expressed as $Q_i = SQ$ and the quantity supplied by other firms can be expressed as $Q_{-i} = (1 - S)Q$. Multiplying the second term on the right-hand side of the above equation with $\frac{Q_{-i}}{Q_{-i}}$ and doing the necessary substitutions, we get

$$-\frac{P}{Q_i}\frac{dQ_i}{dP} = -\frac{P}{SQ}\frac{dQ}{dP} + \frac{(1 - S)Q}{SQ}\frac{P}{Q_{-i}}\frac{dQ_{-i}}{dP}.$$

Noting that $\frac{P}{Q}\frac{dQ}{dP}$ is the market elasticity of demand and $\frac{P}{Q_{-i}}\frac{dQ_{-i}}{dP}$ the elasticity of supply of firms other than i, the elasticity of residual demand on the left-hand side can be expressed as follows:

$$e_{d1} = \frac{1}{S}e_{dm} + \frac{(1 - S)}{S}e_{sj},$$

where the elasticity of firm's demand is expressed as a combination of, e_{dm}, the elasticity of market demand, and e_{sj}, the elasticity of supply of the other firms in the market and the market share firm i has, S.

Remember that the inverse elasticity of residual demand is positively correlated with market power, so the smaller the elasticity of demand, the higher the firms market power. From this equation, Landes and Posner (1981) draw four main conclusions regarding the firm's market power:

1) **The higher the market demand elasticity, the higher firm's demand elasticity and lower its market power.** The higher the market elasticity of demand, the better substitutes the product has and this limits firm's ability to overcharge

2) **The more elastic the supply of competitors, the higher firm's demand elasticity and the lower its market power.** With the highly elastic supply of other firms, the firm in interest has to cut its quantity more to maintain a price increase.

3) **The higher the market share, the lower firm's demand elasticity and higher its market power.** This comes from both the first term and second terms in the above equation. Firstly, the larger proportion of the market the firm has, the less it has to cut its production proportionally to have the same effect on the market. Secondly, the larger firm *i*'s market share is, the smaller the market share of its competitors. Thus, the competitors' increase in supply will have a smaller effect on the market when firm i cuts its quantity.

4) **The market share alone does not tell about the market power.** Market share is only one of the three components affecting firm's market power and elasticities should always be considered as well.

Landes and Posner (1981) note that although the Lerner index (Lerner, 1934) is a good measure of the size of market power, it is extremely hard to estimate. Firstly, marginal costs are an abstract concept and, especially for outside competition authorities trying to measure the markups, it is hard to get a good estimate for the marginal increase in costs resulting from a marginal increase in production when these marginal increases do not happen in reality. A second problem for using the Lerner index is getting reliable measures of elasticities.

Baker and Bresnahan (1988) tackled this problem of measuring the firm's elasticity of demand and in the following we will see how residual demand model for a single firm is derived and what its main advantages are. In addition, we focus our attention on the model's assumptions and bring up some limitations and complications that stem from these assumptions.

3.2. Deriving the Model

Consider the Marshallian demand for firm *i* offering products Q_i. The demand for the product of the firm in question depends on the price of that product, the prices of all other goods that affect its demand and exogenous demand shifters.

$$Q_i = D_i(P_i, P, Y),$$

where Q_i and P_i are the quantity and price of good i respectively, Y includes exogenous demand shifters and P is a vector of prices for other goods affecting Q_i. These other prices include e.g. the prices of competitors and substitutes and these variables depict the supply reaction of other firms. This Marshallian demand function is hard to apply in econometric estimations, as the right-hand side of the equation includes several endogenous variables, P_i and the variables in P, and would thus require an estimation of several simultaneous equations. The amount of equations required could be huge in an industry with product differentiation and due to data limitations the system may be impossible to estimate.

Baker and Bresnahan (1988) developed a way to simplify this equation so that the estimation is made easier and only an estimation of one equation is needed. In the following, we loosely follow Baker and Bresnahan's (1988) derivation of residual demand facing a single firm. The model is made up of three components, the same component that Landes and Posner (1981) recognized as affecting the firm's market power: 1) the inverse demand for the firm in interest, firm 1, 2) the demand equations for all other relevant products affecting the demand of firm 1 and 3) the supply behavior of firms in the market. The quantities of all other relevant products are treated symmetrically, so their supply and demand reactions can be expressed with a single equation. According to Baker and Bresnahan (1988), as the derivation is made for arbitrary demand curves, it can be applied to cases with or without product differentiation. Furthermore, the supply reactions of other firms can vary from perfect competition to that of a cartel.

The inverse demand for firm 1, producing good 1, is

$$P_1 = P(Q_1, Q, Y; \alpha_1),$$

where P_1 and Q_1 are the price and quantity for firm 1's product. Q is a vector of quantities for all other relevant products, i.e. the quantities of competitors and substitutes. These quantities can be set either strategically or independent of firm 1's quantity. Y is a vector of exogenous variables affecting the demand for firm 1. The parameters of the model are contained in α_1.

The second component of Baker and Bresnahan's (1988) model are the equations depicting the inverse demand for all other relevant products, Q

$$P_i = P(Q, Q_i, Y; \alpha_i) \; \forall \; i \neq 1.$$

The third component, supply side equations are included in the model assuming that the other firms are maximizing their profits possibly taking into account the supply of firm 1. Because of profit maximization, marginal revenue must equal marginal costs and we can write the supply side equations as

$$MC_i(Q_i, W, W_i; \beta) = PMR_i(Q, Q_1, Y; \alpha_i, \vartheta_i) \; \forall \; i \neq 1..$$

PMR_i or perceived marginal revenue is the derivative of total revenue and can be written as

$$PMR_i = P(Q_i, Q, Y; \alpha_i) + Q_i \sum_j \frac{dP_i}{dQ_j} \frac{dQ_j}{dQ_i}.$$

Vector W in marginal costs depicts industry-wide factor prices affecting all companies and W_i depicts the firm-specific costs. Cost parameters are included in β. In addition to the inverse demand function, the marginal revenue depends on strategic conduct variables included in ϑ_i, that describe how the supply response of firms other than i affect the price firm i gets from the market.

Taking the supply equations and inverse demand equations of relevant products we can solve for equilibrium quantities in all markets, $i \neq 1$.

$$Q = E^I(Q_1, Y, W, W^I; \alpha_I, \beta_I, \vartheta_I)$$

where the notation I is a union of all variables and parameters for firms i excluding those for the firm in interest. E^I is a vector depicting the equilibriums in each market, i.e. Q is a vector of the equilibrium quantities in all the markets. It should be noted that all elements E_i of E^I are partial reduced form with only one endogenous variable Q_i on the right-hand side and $Q_i = E_i$ for all i ≠ 1. Thus, the elasticities of these equilibrium quantities E_i with respect to the quantity of the firm in interest Q_1 denoted ε_{1i} can be written as:

$$\varepsilon_{1i} = \frac{d \ln E_i}{d \ln Q_1}$$

As $Q = E_i(.)$, we can substitute it into the inverse demand function for firm 1 and get

$$P_i = P(Q_i, E^I(Q_1, Y, W, W^I; \alpha_I, \beta_I, \vartheta_I), Y; \alpha_i)$$

From this, we substitute out the redundancies in variables and use the notation α for the union of α_I and α_1 so that we can write the inverse residual demand function for firm 1 as

$$P_1 = R(Q_1, W, W^I, Y; \alpha, \beta_I, \vartheta_I).$$

Here we have expressed the price for firm 1 as an inverse residual demand function R(.), i.e. as a partial reduced form function of own quantity, demand shifters and both firm- and industry-wide factor prices. The parameter vectors α, β_I, ϑ_I are functions of the parameters of the structural equations.

As we are interested in the elasticity of residual demand, denoted $1/n_1^R$, we differentiate the previous equation in logarithms.

$$n_1^R = \frac{d \ln R}{d \ln Q_1} = \frac{d \ln P_1}{d \ln Q_1} + \sum_{i \neq 1} \frac{dP_1}{dQ_i} \frac{dQ_i}{dQ_1}$$

so that

$$n_1^R = n_{11} + \sum_{i \neq 1} n_{1i}\, \varepsilon_{1i},$$

where n_1^R is the inverse elasticity of residual demand i.e. the reciprocal of firm's elasticity of demand that we explained to represent the markup percentage. The first term on the right-hand side of equation captures the direct effect the quantity changes have on the price firm 1 gets in the market. The second term on the RHS is reciprocal of the sum of the supply elasticities of all the other firms in the market and it captures the competitive response of other firms to the quantity changes of firm 1.

We see that elasticity of residual demand depends on the market elasticity of demand and the price elasticity of supply of other firms, identical to Landes and Posner (1981). Here we can note the same characteristics between elasticity and market power as we did earlier.

As stated earlier, a non-zero elasticity of residual demand implies market power and a positive markup. However, Baker and Bresnahan (1988) point out that the relationship between markups and n_1^R are not always clear. According to Baker and Bresnahan (1988), firms in consistent conjectures equilibrium will assume correctly their competitors' reactions and the effect the reactions will have on their demand, so the elasticity of residual demand is a correct measure for their markup.

The term "consistent conjectures", as defined by Bresnahan (1981), relates to the assumptions a firm in an oligopoly setup has about the strategic decision making of its competitors. The conjectures are consistent when they are correct not only on the levels of strategic variables but also on the decision-making process leading to these levels. When setting prices, the firms set their prices according to the demand curve they think they are facing. For firms in Consistent Conjectures Equilibrium, this demand curve is the same as the one they face in reality, and thus for these firms we can state that

$$-n_1^R = \frac{P_i - MC_i}{P_i}.$$

The right-hand side of this equation is the Lerner-index (Lerner, 1934) that measures market power with the markup percentage. To see more clearly why this relationship does not always hold, let's look back to the equation for n_1^R

$$n_1^R = n_{11} + \sum_{i \neq 1} n_{1i}\, \varepsilon_{1i}.$$

We may think of ε_{1i} as the conjectures firm 1 has about the reaction of competitive supply fringe to changes in firm 1's quantity. When these conjectures are not consistent with reality, the firm does not set its markup according to elasticity of residual demand that we get from our estimations. Instead, the firm acts as if ε_{1i} was something else.

A common example of non-consistent conjectures equilibrium is the basic Cournot-case with constant marginal costs. Here the firms take the supply of other firms as constant and maximize their quantities subject to this quantity. Quantities are assumed to be independent, when in reality, the supply of the other firm depends on the supply of the other firms as defined by reaction curves. In other words, the firms act like $\varepsilon_{1i} = 0$ when in reality it is a function of the other firms output. If one firm deviates from the equilibrium, it has a wrong idea about the reaction the other firm will have on this deviation.

Consistent conjectures literature has faced much criticism and the whole idea is claimed paradoxical. For the conjectures to be correct, one player should perfectly predict the actions of the other player. These actions, in turn, are based on perfectly predicting the actions the other player. If one player deviates from the Nash equilibrium, the other player has already wrongly predicted the actions and there cannot be any consistency in conjectures. If, on the other hand, the players stay in the Nash equilibrium, the conjectures of constant output are locally correct. (Lindh, 1992).

From all this we conclude that while the elasticity of residual demand might not give a perfect picture of the market power in all oligopoly setups, it does give us a close estimate of the markups firms charge. For a dominant firm, the estimate is correct and for others, the estimate is the upper limit of market power the firm can have (Baker and Bresnahan, 1988).

3.3. Estimation Specification

In the previous, the following inverse residual demand function was derived

$$P_1 = R(Q_1, W, W^I, Y; \alpha, \beta_I, \vartheta_I)$$

and it was explained how the elasticity of this function with respect to Q_1 can be used to infer market power in terms of markup. The residual demand equation is often estimated in the inverse form, but it could be derived and estimated with quantity as the left-hand side variable as well. The inverse demand is chosen more often, as this allows us to conduct a one-sided hypothesis test of no market power, i.e. the null hypothesis of $dP_1/dW_1 = 0$ (Björkroth et al., 2006). This null hypothesis implies that there are no possibilities for a potential monopolist to raise prices when firm-specific costs change.

To get the elasticities, the above equation is usually estimated in double logarithms. Denoting natural logarithms of variables with a lower case letter, the common equation for estimation, presented for example in Baker and Bresnahan (1988), is of the form

$$p_1 = \beta_0 + \beta_1 q_1 + \sigma W + \delta Y + u_{d1},$$

where σ and δ are the parameter vectors for cost and demand variables respectively and W is a matrix containing all the cost-side variables, both firm-specific (W^1) and industry wide (W^I). Y is a matrix containing all the demand side variables and u_{d1} is an IID error term.

It should be noted that the equation has an endogenous variable on the right-hand side as the price and quantity are determined simultaneously by supply and demand functions and they affect each other. This breaks the basic assumptions of ordinary least squares (OLS) estimations and will cause problems in the estimators. In the next part, we will discuss these and other problems related to estimations and how we may address them.

4. Methods

As always when analyzing demand, simultaneous equations methods are important, and in this study we will focus especially on two stage least squares methods (2SLS). In the residual demand literature, also three stage least squares (3SLS) has frequently been used and it will be reviewed shortly in this section as well. Unlike other papers written about residual demand, this paper also focuses on stationarity - one of the most important topics in current time series econometrics. We will discuss that and related topics that help us in taking into account potential nonstationarity in the series.

4.1. Simultaneous Equations Methods

Simultaneity bias, or simultaneous equations bias, is caused when two or more variables in classical OLS estimation have a two-way relationship so that they both affect each other. In the case of demand analysis, price and quantity are simultaneously determined, and thus affect each other. Using OLS in our setup, the error term would be correlated with both the price and quantity and this breaks the basic assumptions of OLS and makes the estimators biased.

Simultaneity bias can be avoided by doing the estimations with an instrumental variable (IV) method or as a 2SLS estimation. 2SLS will provide asymptotically unbiased estimators. In IV-estimation one or more exogenous variables correlated with the endogenous variable on the right-hand side, but not with the error term, are used as an instrument for an endogenous variable. Thus, the instrument, denoted z, must satisfy the following conditions

$$cov(z, u) = 0$$

and

$$cov(z, x) \neq 0,$$

where x is the problematic endogenous variable that is instrumented with z and u is the error term in the original estimation equation. In other words, to identify the reduced form equation for the endogenous variable, we need a variable that we find only in the equation for that specific endogenous variable and not in the original equation.

In 2SLS, the IV-estimation is done in two stages: at the first stage, the endogenous variable on the right-hand side is regressed with OLS on all the exogenous variables on the right-hand side plus the instrumental variables. The fitted value from this 1st stage estimation provides us with a reduced form expression of the problematic variable, i.e. that variable expressed in terms of exogenous variables. By definition, the exogenous variables are uncorrelated with the error term and as the fitted value is a linear combination of these variables, it too must be uncorrelated with the error term. At the second stage of the estimation, the endogenous variable is replaced by its fitted value.

To see this process more clearly, let's consider the residual demand model presented by Baker and Bresnahan (1988):

$$p_1 = \beta_0 + \beta_1 q_1 + \sigma W + \delta Y + u_{d1}.$$

As stated earlier, q_1 is endogenous and correlated with the error term u_{d1} because of simultaneity of p_1 and q_1. The other variables are exogenous.

At the first stage, we regress q_1 with all the exogenous variables on the right-hand side, including the constant term, and the instrumental variables.

$$q_1 \ = \alpha_0 + \alpha_1 Z + \alpha_2 W + \alpha_3 Y + v_{d1},$$

where Z is a vector of instrumental variables and α_i, $i = 0,1, 2, 3,$ are parameter vectors. As all the variables on the RHS of the above equation are exogenous, the covariance between them and the error term must be zero. Thus, the fitted value of q_1 , q_1^* is expressed as a linear combination of independent exogenous values. Now we can substitute the quantity variable in the original model with the fitted value and get:

$$p_1 = \beta_0 + \beta_1 q_1^* + \sigma W + \delta Y + u_{d1}.$$

As q_1^* is clearly exogenous, this equation does not have any endogenous variables on the right-hand side and it can be estimated normally using single-equation techniques.

As stated earlier, instrument variables must be exogenous. If there are more than one instrumental variable per an endogenous variable, Sargan's test for overidentification restrictions can be used. In Sargan's test, the null hypothesis is that all the instruments are exogenous. The alternative hypothesis then is that at least some of the IVs are not exogenous. The test is conducted in the following way:

1. Estimate the structural equation by 2SLS and save the residuals.

2. Regress the saved residuals on all exogenous variables, including the instruments. Obtain R^2 from this equation.

3. Compute nR^2.

Now, the critical values are obtained from chi-squared distribution, $nR^2 \sim \chi$, where the degrees of freedom is the number of exogenous variables from outside the model less the total number of endogenous variables. If the chi-squared value exceeds the critical value, H0 is rejected. The intuition is that we want to check whether there is significant correlation between the instruments and the residuals, as this would tell us that the hypothetical exogenous variables are in fact endogenous. It should be noted that if the overidentification restrictions are rejected by Sargan's test, we do not know which of the restrictions failed the test, only that the combination is not working.[3]

In addition to the above condition of exogeneity, the instruments must also have high relevance - the instruments should be able to explain the instrumented variables. Otherwise the fitted value given by the first stage estimation will be only a linear combination of the exogenous values and there will be a problem of multicollinearity at the second stage. Multicollinearity will result in high standard errors in the estimates and make the estimates less reliable, meaning that small changes in the sampled data can lead to large changes in the coefficient values.

It should be noted that as IV and 2SLS provide only asymptotically unbiased estimators, and with small samples, the estimators can still be biased. However, the direction of

[3] For examples and further discussion consult e.g. Brooks (2008)

2SLS bias in residual demand estimations can be chosen by choosing the left-hand side variable correctly. If the variance of costs is greater than or equal to the variance of the error term, the OLS coefficients are biased towards zero (Froeb and Werden, 1999). This will lead to more conservative results with respect to the existence of market power.

Three stage least squares (3SLS) method, originally presented by Zellner and Theil (1962) is often used in residual demand estimations (see e.g. Baker and Bresnahan, 1988 or Yang, 2001). 3SLS combines 2SLS with seemingly unrelated regression equations (SURE) that takes into account the covariances between the errors in each residual demand function estimated. SURE method generally provides more efficient estimates when the errors are correlated also the 3SLS estimators are generally more efficient.[4]

In many studies, e.g. Baker and Bresnahan (1988), 2SLS is found to provide results very similar to 3SLS but this naturally depends on the relationship between the equations at hand.

4.2. Stationarity

Much of the statistical inference regarding stochastic processes, also those done with the above mentioned simultaneous equations methods, depend on the assumption that key summary statistics of the data generating process – its mean, variance and covariance - remain constant through time. This feature of the stochastic process is referred to as covariance stationarity.[5] Stationarity is also one of the underlying assumptions of linear regression. For nonstationary processes, linear regression can lead to a spurious regression, where the residuals contain a stochastic trend, the power of t-test is diminished and hypothesis testing cannot be conducted reliably (Granger and Newbolt, 1974).

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[4] For further discussion on 3SLS, see e.g. Greene (2000)

- Stationarity and Unit Root Testing chapters are largely based on Enders (2010) and Brooks (2008)

[5] From here on, covariance stationarity and stationarity are used interchangeably, as weak stationarity is a sufficient condition for the analysis done in this paper.

For a stochastic process to be stationary, the following conditions must hold for all time periods t:

$$E(y_t) = \mu$$

$$var(y_t) = \sigma^2$$

$$cov(y_t, y_{t-s}) = cov(y_{t-j}, y_{t-j-s}) = \gamma_s \; \forall t, j, s \in I,$$

where μ, σ and γ_s are constants.

4.3. Unit Root Testing

The stationarity of a series is usually tested with unit root tests, as a series with a unit root is always nonstationary. A series is said to have a unit root if the root of its characteristic equation lies outside of the unit circle. A basic example of a series with a unit root is the series developed by a random walk process. The random walk process is defined as follows:

$$y_t = y_{t-1} + error_t.$$

The characteristic equation of this process, denoting lag operator with L, is

$$1 - L = 0$$

and it clearly has a unit root. The random walk process is thus nonstationary.

Nonstationary series can sometimes be made stationary by differencing them.[6] For example, the random walk process is made stationary by differencing it once, i.e. subtracting y_t from both sides of the equation:

$$Dy_t = error_t.$$

[6] Note that this is not the case if the series is trend stationary, i.e. the process has a deterministic trend. In such a case, differencing will lead to unwanted behavior in the errors. However, we will focus on difference stationary series as generally economic and financial series are found to be such.

As $error_t$ follows a white noise process, the first difference of random walk is clearly stationary. As the random walk can be made stationary by differencing it once, the series is said to be integrated of order 1, denoted $y_t \sim I(1)$. More generally, an I(d) process has to be differenced a minimum of d times to make it stationary.[7]

The existence of unit root in a stochastic process can be tested by Dickey-Fuller (DF) type tests. DF tests test an equation of the following type

$$Dy_t = a_0 + a_1 t + \gamma y_{t-1} + error_t,$$

where a_0, a_1 and γ are parameters and D is the difference operator. Depending on the specification of the test, a_0 and a_1 can be either set to zero or included in the equation. The null hypothesis of DF test is that $\gamma = 0$, i.e. that the process has a unit root and is nonstationary. The alternative hypothesis is that $\gamma < 0$ and the process is I(0). The equation is estimated using OLS and the test statistic is calculated as:

$$\tau = \frac{\hat{\gamma}}{Std.Err.(\hat{\gamma})},$$

where $\hat{\gamma}$ is the OLS estimator for γ. The test statistic follows a Dickey-Fuller distribution and the critical values, drawn from simulations, depend on the specification of the test and of course on the degrees of freedom.

DF-test assumes that the true data generating process is a first order autoregressive process, denoted AR(1). This means that the current value of the series depends only on the previous value of that series. DF test can be further augmented by including lagged difference terms to account for a more complicated data generating processes. Neglecting the true complexity of the process would result in autocorrelation in the residuals, but with the augmented test the autocorrelation can be avoided. This sort of

[7] Note, however, that I(0) is only a necessary condition for stationarity, not a sufficient condition. Still, a I(0) series is usually considered stationary in econometric analyses.

test is called Augmented Dickey Fuller (ADF) test and the test equation is of the following form:

$$Dy_t = a_0 + a_1 t + \gamma y_{t-1} + \sum_{i=t-1}^{t-p+1} \sigma_i Dy_i + error_t,$$

where a_0, a_1, γ and σ are parameters and a_0 and a_1 can be again either set to zero or included in the equation. Again, t refers to time period and p is the number of lagged differences included in the test. The test procedure and the hypothesis tested are the same as with regular DF-test.

The ADF test is sensitive to choosing the correct number of lags. Too few lags do not remove all the autocorrelation in the process, and too many, on the other hand, lead to a lower power of the test as the degrees of freedom are eaten up by unnecessary lags. Optimal lag length can be chosen by using an information criterion, for example Schwarz Bayesian Information Criterion (BIC), so that the lag length that minimizes the criterion is considered optimal. Some sources (e.g. Brooks, 2008) suggest a simple rule of thumb of using 12 lags for monthly data, 4 for quarterly and so on.

4.4. Cointegration and Error Correction Models

Differencing can provide a solution to problems related to stationarity, but it can also lead to a loss of information. Consider the following model:

$$y_t = a_0 + a_1 z_t + error_t.$$

Differencing it once gives:

$$Dy_t = a_1 Dz_t + Derror_{t.}$$

By definition, in the long-run steady state

$y_t = y_{t-1} = y^*$

and

$z_t = z_{t-1} = z^*$

for all t, so

$$Dy_t = Dz_t = 0.$$

Thus, differencing loses all information about a long run solution. In many economic models, the long-run equilibrium is of great interest, and loosing this information can be a significant loss to analysis.

Generally, if two series are integrated, their linear combination has an order of integration equal to that of the largest order of integration of the two. However, for two cointegrated series, the linear combination is of lower order of integration than the series themselves. Engle and Granger (1987) defined cointegration in the following way:

"The components of the vector x_t are said to be co-integrated of order d, b, denoted $x_t \sim CI(d,b)$, if (i) all components of x_t are I(d); (ii) there exists a vector $\alpha(\alpha \neq 0)$ so that $z_t = \alpha' x_t \sim I(d-b)$, $b>0$. The vector α is called the cointegrated vector."

Thus, for series to be cointegrated, they must have the same order of integration and there must be one or more linear combinations of those series that have an order of integration lower than the order of integration that those series have independently. Cointegration is in essence a long run relationship that series have and that ties them together in the long run.

Engle and Granger (1987) proposed a 2-step procedure to test for cointegration, find the cointegrated vector and building an error correction model:

1. Estimate a static cointegrated vector. Obviously, the series in the vector should be of the same order of integration to fulfill the conditions set in the definition above. Next, the estimated residuals are tested for no cointegration. This can be done by, for example, an ADF test. As the test is done for estimated error terms and not actual series, the usual critical values for ADF given by, for example, most statistical software will not do, but one should use those simulated by MacKinnon(1991).

2. Include the lagged residuals from step one in the error correction model. This is the same as including the cointegrated vector in the model.

If a cointegrated vector is found, a so-called error correction model including that vector and the integrated variables in their differenced forms can be built. If, on the other hand, no cointegrated vector is found, no long-run solution exists and using a basic differenced model loses no information.

Brooks (2008) has summarized the critique for the above mentioned procedure.

1. The unit root and cointegration tests are not powerful in finite samples so that one cannot be certain whether there is a cointegrating relationship or not.

2. The cointegrated vector treats the variables asymmetrically, assuming a direction of causality. This might influence the results, i.e. the residuals saved from the first step even if theoretically there should be no difference between the chosen dependent variable.

3. Hypothesis tests cannot be done with the actual cointegrating relationship in step 1.

In addition, the Engle-Granger 2-step method is sensitive to misspecification in the first step as any mistakes in this step are carried on to the second step. Johansen's (1988) method estimates the CI vector simultaneously with the error correction model and thus counters the misspecification problem. It also avoids problems 2 and 3 in Brooks (2008) list. Furthermore, it allows for more than one cointegrating relationship between the variables in cases where there are more than two variables in the model.

Johansen's method is based on vector autoregressive (VAR) specification. VAR models can be viewed as hybrids between simultaneous equations and univariate time series models. Whereas in univariate cases we assume that the current value depends only on the processes values in different time periods, in VAR there are several variables that depend on their own past values and the past values of other variables. This also means that VAR models do not discriminate between endogenous and exogenous variables - all variables are considered endogenous and determined simultaneously.

For example, a VAR model with g variables and k lags might look the following:

$$y_t = \beta_1 y_{t-1} + \beta_2 y_{t-2} + \cdots + \beta_k y_{t-k} + u_t,$$

where β_j is a (gxg) matrix of parameters for variables at time t-j and y_i is a (gx1) matrix of variables at time *i, i = t-1, ..., t-k.* Assuming that y_t ~I(1), the above VAR model can be turned into a vector error correction model (VECM) (Johansen, 1988).

$$Dy_t = \pi y_{t-k} + \sum_{i=1}^{k-1} G_i\, Dy_{t-i} + u_t,$$

where $\pi = \sum_{i=1}^{k}(\beta_i \; - \; I_g)$ and $G_i = \sum_{j=1}^{i}(\beta_j \; - \; I_g)$, I_g being an (gxg) identity vector

To find the number of cointegrated vectors, we inspect the rank of π. The rank of a matrix is equal to the number of its eigenvalues, so the number of nonzero eigenvalues π has equals the number of cointegrated vectors the process has. If the rank of π is zero, it has no elements and there is no cointegrating relationship between the variables.

Johansen's (1988) tests of cointegration focus on finding these non-zero eigenvalues for π, denoted $\lambda(i)$, where i refers to the ith eigenvalue when they are ordered in ascending order. Johansen (1988) presents two test statistics:

$$\lambda_{trace}(r) = \; -T \sum_{i=r+1}^{g} \ln(1 - \hat{\lambda}_{r+1})$$

and

$$\lambda_{max}(r, \; r+1) = \; -T \; \ln(1 - \hat{\lambda}_{r+1}),$$

where T is the sample size, r is the number of cointegrated vectors under the null hypothesis and $\widehat{\hat{\lambda}_\imath}$ is the estimated value for ith largest eigenvalue. A significantly positive eigenvalue indicates a significant cointegrated vector.

The first test, a so-called trace test, tests the joint significance of

$H0\!: rank(\pi) \leq r \;\; vs. \;\; H1\!: rank(\pi) > r$

In other words, the null hypothesis is that the number of cointegrated vectors is less than or equal to r. The second test, maximum eigenvalue tests, tests each eigenvalue separately and has a null hypothesis that the number of cointegrated vectors is r against an alternative that there are r+1 vectors. The test procedure in maximum eigenvalue test is such that at first, the null hypothesis is $H0: r=0$ vs. $H1: 0<1 \leq g$. If the null is not rejected, the value of r is increased as long as the null is not rejected or that the null is $r=g-1$.

The critical values for both these tests can be found in Johansen and Juselius (1990) and they depend on the number of variables in the model and the rank of π. Similar to DF-tests, constant and drift terms can be included in the model and these again affect the critical values.

Although Johansen's methodology is typically used in a setting where all variables in the system are I(1), having stationary variables in the system is theoretically not an issue (Johansen, 1995) . Thus, there is little need to pre-test the variables in the system to establish their order of integration. If a single variable is I(0) instead of I(1), it will reveal itself through a cointegrated vector made up of only the stationary variable.

5. Earlier Residual Demand Estimations

The concept of residual demand was first applied in econometric estimations for US brewing industry by Baker and Bresnahan (1988) when they estimated the elasticity of residual demand for three big beer producers in US. After that, residual demand has been used in many situations. For example, Yang (2001) evaluated the market power of US primary and secondary aluminum industry and estimated the residual demand curve for the whole industry, not a single firm. In this part, we focus on problems in residual demand analysis and solutions to them found in literature.

5.1. Instrumental Variable Choice

Firm's own quantity, which is endogenous according to the model specification, needs to be instrumented to avoid simultaneity bias as we discussed in part 4. Not taking into account the endogenous own quantity, the OLS estimates would be biased downwards and provide conservative estimates for market power, i.e. market power would be disproved more easily (Baker and Bresnahan, 1988).

Typically the variables used as instruments for firm's own quantity have been proxies for firm-individuated factor prices. Baker and Bresnahan (1988), for example, used both capacity and average capacity as instruments. These instrument variable choices are well justified: as capacity investments are done infrequently and in large amounts, capacity is exogenous in the short-run. Capacity is also correlated with marginal costs as with high capacity, the marginal costs are lower than when capacity is constrained. Average capacity, on the other hand, represents the use of plant level economies of scale that also alter marginal costs. As one of the firms had production facilities only in one region, the regional manufacturing wages in that region could be used as an instrument for that firm. They represented the independent movements in costs for that firm, as the industry-wide wages were included in the cost variables as well. Baker and Bresnahan emphasized that if firm-individuated factor prices are not available, the residual demand curve will not be identified. (Baker and Bresnahan, 1988.)

5.2. Unstable Market Environment and Dynamics

Foreb and Werden (1999) point out how nonstationarity is a problem for the utility of residual demand analysis. By nonstationarity, Froeb and Werden (1999) do not directly refer to the statistical concept that we discussed and noted as a flaw in the residual demand estimations in the previous part. In their setup, nonstationarity refers to more general instability in the demand and cost conditions in the market. If we cannot assume that the market conditions remain the same in the future, it limits the inferences that we can draw from the residual demand estimations.

In a stable environment with steady demand and cost conditions, nonstationarity regarding the future values might not be a big problem. However, Froeb and Werden (1999) present two reasons why the instability of the market environment should be considered especially in merger cases. Firstly, changing market conditions can make mergers profitable and thus mergers can be seen as a result of changes in the market. Secondly, a merger proposal is more likely to get an approval from the antitrust authorities when the conditions are changing. This is because it is more difficult for the antitrust authorities to estimate the effects of the merger on market power based on historical data when the environment is turbulent. What these two points mean is that mergers themselves can be viewed as a sign of an unstable environment regarding demand and costs and nonstationarity issues should be taken into consideration when using the elasticity of residual demand in predicting the future.

Dynamics bring yet another problem into residual demand analysis. Each observation of prices and quantities is easily assumed to be a static equilibrium between supply and demand when in reality the observations can be a result of a dynamic process where past prices or quantities or expected future prices can affect the prices in the current period.

Froeb and Werden (1999) give the following example of how buyers' ability to inventory can show up as spikes in demand. If a price increase seems temporary, a buyer with inventories will cut its demand drastically. When the price level remains high for a longer time, the buyer will increase its demand as its inventories start to run low. Similarly, we can see how expected lower prices in the future, caused for example by events that decrease producers' costs and increase the supply, can cause a buyer with inventories to postpone its demand for the next period. Persisting higher prices will also affect buyers' willingness to find substitutes and suffer potential switching costs, which again lead to larger quantity reductions in the long-term than what a short-term demand analysis might suggest. Thus buyers' ability to inventory and learn can either under- or overestimate firm's ability to affect prices through quantity reductions. Estimates that do not correctly and explicitly account for these dynamic effects will be biased. (Froeb and Werden, 1999). As the true dynamic process can never be truly known, some bias is bound to exist in any estimate for the elasticity of residual demand.

6. Data and Tests

In this part, the data is presented and several tests and summary statistics are calculated based on that data. Probably the most interesting tests in this part, from the point-of-view of our analysis, are the ADF tests done in the latter parts of this chapter. These tests are generally neglected in the literature.

6.1. Data

The analysis is done with monthly data ranging from January 2004 to December 2010 and including 84 observations. All the sales prices and quantities come from UPM's databases. Cost side data used in this study are public, coming from the Finnish Forest Institutes statistics databases or from Statistics Finland. Demand side data for Finnish markets come from Statistics Finland. To capture the elasticities straight from the estimations, all the variables are transformed into logarithms.

All the variables used in this study can be found in the Table 2 below. Note that all the variables are in logarithms. Real prices and costs were generated by deflating the nominal counterparts with consumer price index. For estimations with Johansen's method, we used nominal prices and costs instead of real ones.

Table 2 Variables used in the study

	Variable Name	Meaning
Prices	price 1	Real Price of Wood type A Center Good Product Group (Product 1)
	price 2	Real Price of Wood type B Center Good Product Group (Product 2)
	price 3	Real Price of Wood type A Board Product Group (Product 3)
	price 4	Real Price of Wood type B Board Product Group (Product 4)
UPM's Quantities	quantity 1	Quantity Sold of Wood type A Center Good Product Group (Product 1)

	quantity 2	Quantity Sold of Wood type B Center Good Product Group (Product 2)
	quantity 3	Quantity Sold of Wood type A Board Product Group (Product 3)
	quantity 4	Quantity Sold of Wood type B Board Product Group (Product 4)
Demand	fin_bkt	Real GDP for Finland
	fin_const_permits_quartal	The Number of Construction Permits Issued in the Current Quarter (Extrapolated for each month)
	fin_construction_starts_quartal	The Number of Construction Starts Issued in the Current Quarter (Extrapolated for each month)
Costs	real_stumpagep_Alog	Real Stumpage Prices of Wood type A Log
	real_stumpagep_Blog	Real Stumpage Prices of Wood type B Log
	real_stumpagep_Alog_ks	Real Stumpage Prices of Wood type A Log in Kymi-Savo Region
	real_stumpagep_Afiber	Real Stumpage Prices of Wood type A Fiberwood
	real_stumpagep_Bfiber	Real Stumpage Prices of Wood type B Fiberwood
	real_man_costs_saw	Real Production Price Index for Sawmilling
	real_man_costs_industry	Real Production Price Index for Industrial Production
Instruments	production	UPM's Total Production of Sawn wood
	production_B	UPM's Total Production of Wood type B Sawn wood
	production_A	UPM's Total Production of Wood type A Sawn wood
	sek	EUR/SEK Exchange Rate
	gbp	EUR/GBP Exchange Rate

The relevant cost variables for UPM's residual demand model are assumed to be stumpage prices for sawn wood logs and the producer price index for sawmilling that represent industry wide costs. For wood type A, UPM's major sawmill located in Lappeenranta allows us to use the stumpage prices of that specific region to identify UPM-specific costs. The prices in that region are naturally closely correlated with the overall prices in Finland, but not perfectly. From the demand side the number of construction permits can be assumed to affect prices of sawn wood as construction is one of the major demand drivers and construction permits anticipate the future demand. Another related variable, the number of housing starts is tested as well, but found to be less significant. Real GDP can also be seen as a major influence on sawn wood prices as sawn wood markets are generally described as sensitive to economic cycles.

As discussed earlier, there is reason to believe that stumpage prices are endogenous, i.e. depend on the price of sawn wood, as UPM is one of the three large buyers in the raw material market. Also some of the earlier studies point in this direction. To account for this possible endogeneity, the lagged values of cost factors are used. Using lagged values can be justified also by the fact that production happens in earlier periods than sales and thus, the lagged values of costs are in fact the relevant cost side variables. Still, all the endogeneity might not be removed from this, since an expected rise in the future sawn wood prices can increase UPM's willingness to pay for sawn wood, which may drive up the stumpage prices.

All the insignificant variables are not removed from the model as in some cases the zero results can be interesting as well. This is the case especially when a variable we assumed to be significant turns out insignificant. Some of the variables might experience collinearity. Removing collinear variables can change the coefficients of other variables and this is something that should be taken into account already when building the model.

From Table 3. we see that the correlations between prices and their respective quantities are rather low ranging from -0,35 to near zero. Especially for board products, products 3 and 4, the correlations between prices and quantities are practically zero.

Without correlation there cannot be any causality, so there cannot be any pricing power either. Still, estimations are done for those products as well to see how cost variables affect the prices and to further verify this result of no market power.

Table 3. Correlations between prices and quantities sold.

	Product 1_m3	Product 2_m3	Product 3_m3	Product 4_m3
price 1	-0.3538	-0.2422	0.1741	0.2498
price 2	-0.1618	-0.1602	0.2670	0.2801
price 3	-0.2976	-0.4408	0.0481	0.1491
price 4	-0.4162	-0.4175	0.0166	0.0627

In Table 4 below, summary statistics for the variables used can be found. Note that the variables are in logarithms. The center goods (products 1 and 2) are more expensive and have a higher variance in prices than boards.

Table 4. Summary statistics for the main variables; UPM's quantity sold and real prices

Variable	Obs	Mean	Std. Dev.	Min	Max
quantity 1	84	6.459491	.9560774	4.352945	7.894813
quantity 2	84	6.933079	.9839156	2.415735	8.537629
qauntity 3	84	7.545965	.39088	6.56943	8.217656
quantity 4	84	7.972111	.4805967	5.519026	8.715787
price 1	84	4.924614	.1233624	4.558481	5.197965
price 2	84	5.069521	.1297663	4.720509	5.395073
price 3	84	4.516862	.1593114	4.341677	4.976228
price 4	84	4.661632	.1761075	4.407116	5.083102

6.2. Instrumental Variables

To account for the simultaneity between prices and quantities, instrumental variables need to be found. If firm individuated factor prices are not observed, no instruments will be available to estimate firm's elasticity consistently. Using OLS will result in parameter estimates that are subject to simultaneous equation bias, as explained earlier.

A potential instrumental variable in our study is the total amount of sawn wood produced by UPM. UPM's total production describes how costly the production of sawn wood is, and thus describes how the marginal costs for a specific product develop. Furthermore, the correlation of total production with the price of a specific product is likely to be low assuming that the prices for different products move independently. Exchange rates between Euro and other currencies are exogenous for a single firm but still affect the costs of production. This can make them good instrumental variables. The reasons why separate exchange rates might work as instruments must be judged case-by-case.

Woodchips are a significant by-product in sawn wood production. The internal and external sales of wood chips make up a significant share of the total sales of UPM's sawn good production making it a significant factor in determining the costs of sawmilling. UPM's woodchip prices are not available for the whole observation period of our study and we cannot use them as instruments. The price of fiberwood, on the other hand, can be seen as proxy for the price of woodchips as woodchips and fiberwood are close substitutes in pulp production. Thus fiberwood stumpage prices may be good instrumental variables. Especially from the point-of-view of boards, the connection between woodchip, fiberwood and sawn wood prices is extremely interesting, as low quality boards can be turned into woodchips if the price of woodchips and fiberwood climbs high enough. The price of fiberwood can thus be seen as determining a price floor for the lowest quality products.

A correlation matrix, presented in Table 5, was calculated to see how different variables would fulfill the conditions for an instrumental variable. The matrix clearly shows that total production and exchange rates could be good instruments. Unfortunately the fiberwood stumpage prices were highly correlated with the sawn wood price and could thus not be used as instruments. Still, it might be worthwhile to include them in the estimations for boards. For the lagged values of the same variables, the correlations were similar but generally the current period values were found more correlated with quantity and less with price suggesting that current values would be better instruments in our 2SLS estimations. Still, as the lagged values are more likely to be exogenous based on the above argumentation, we will test both as instruments and base our decision of instrumental variables on postestimation tests.

Table 5. Correlations between prices, quantities and the chosen instrumental variables.

Correlations	production	production_B	production_A	sek	gbp
price 1	0.02	-0.04	0.06	-0.19	0.11
price 2	0.13	0.07	0.16	-0.38	-0.12
price 3	0.01	-0.06	0.05	0.01	0.12
price 4	0.00	-0.06	0.04	-0.11	0.15
quantity 1	0.41	0.44	0.35	-0.40	-0.70
quantity 2	0.44	0.48	0.38	-0.57	-0.58
quantity 3	0.49	0.45	0.47	-0.62	-0.71
quantity 4	0.54	0.53	0.50	-0.53	-0.55

6.3. **Stationarity Tests**

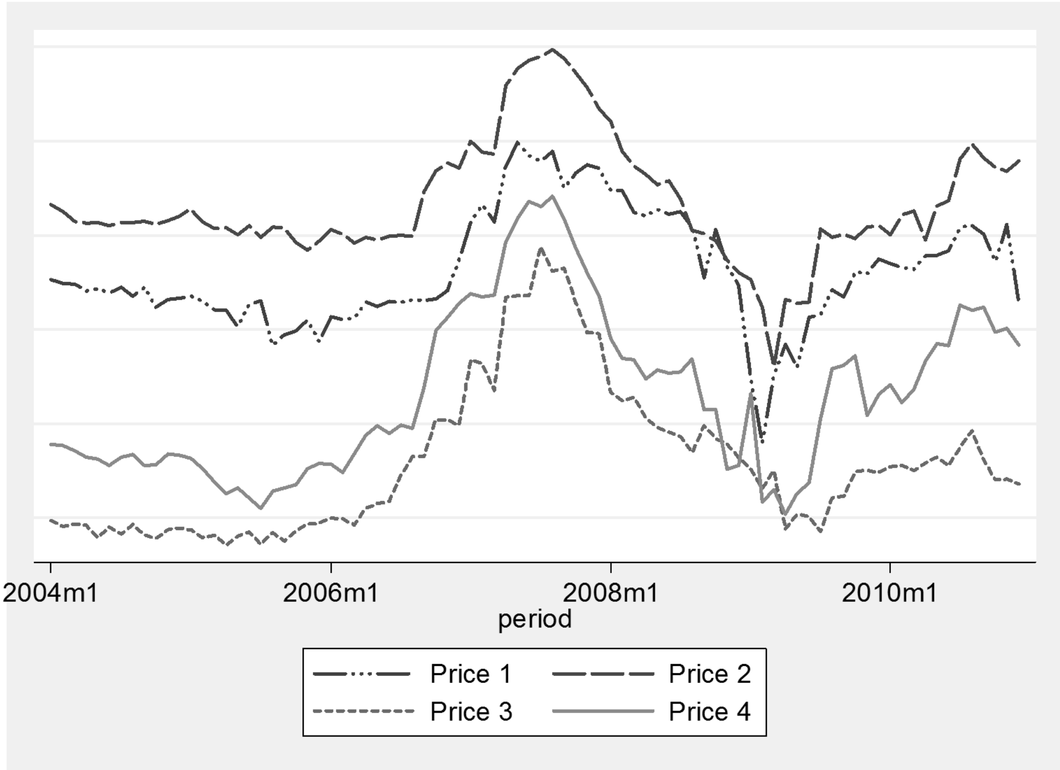
Regardless of the importance of stationarity, it is not taken into account in residual demand literature. This study expands the current residual demand literature by offering a way to account for this.

ADF is not a very powerful test and one should be cautious when drawing inferences when the test statistic is close to critical values. If the tests are not clear, the robustness of inferences can be tested by treating the variables as both stationary and nonstationary and seeing how this affects the results. In our estimations, we will treat the series as both I(1) (Johansen's method) and I(0) (2SLS) to see how this affects the results.

Stationarity was tested with DF-GLS test where the ADF test equation is turned into GLS form before estimation. The tests, found in Appendix 1, were done for lags 1-11, where the maximum lag was decided with Schwert criterion. The optimal lag length was decided based on two information criterion: BIC and MAIC. Usual ADF tests were also done, although not presented here, using twelve lags as suggested by Brooks (2008). The tests showed how sensitive ADF tests are to different lag lengths and specifications; including a trend or leaving out a constant provided conflicting results.

Graphical examination was also needed to determine the order of integration of the variables. The large spike in the middle of our observation period that is due to overheating in the sawn wood markets can also affect our ADF tests results. Graphical examination of price series in Figure 9 shows that at least the boards (the lowest two lines of the upper picture) experience a slight upwards trend. The differenced series in the lower picture, on the other hand, are clearly stationary. The graphs of other variables can be found in Appendix 1. Depending on the information criteria used, the ADF tests sometimes showed conflicting results, but based on both the ADF tests and graphical examinations (see Appendix 1), the variables used in this study were found to be I(1).

Although the autocorrelation (ACF) and partial autocorrelation functions (PAC) are not defined for nonstationary series, we can still try to use them to give us hints of the data generating process at hand. The correlograms in Appendix 1 show that the first lag of real prices seems to have a high spike in the PAC and the ACF is slowly decaying to zero. This can point to an AR(1) process and we will later take this into account in our 2SLS estimations by including a lagged price variable on the RHS of the equation.



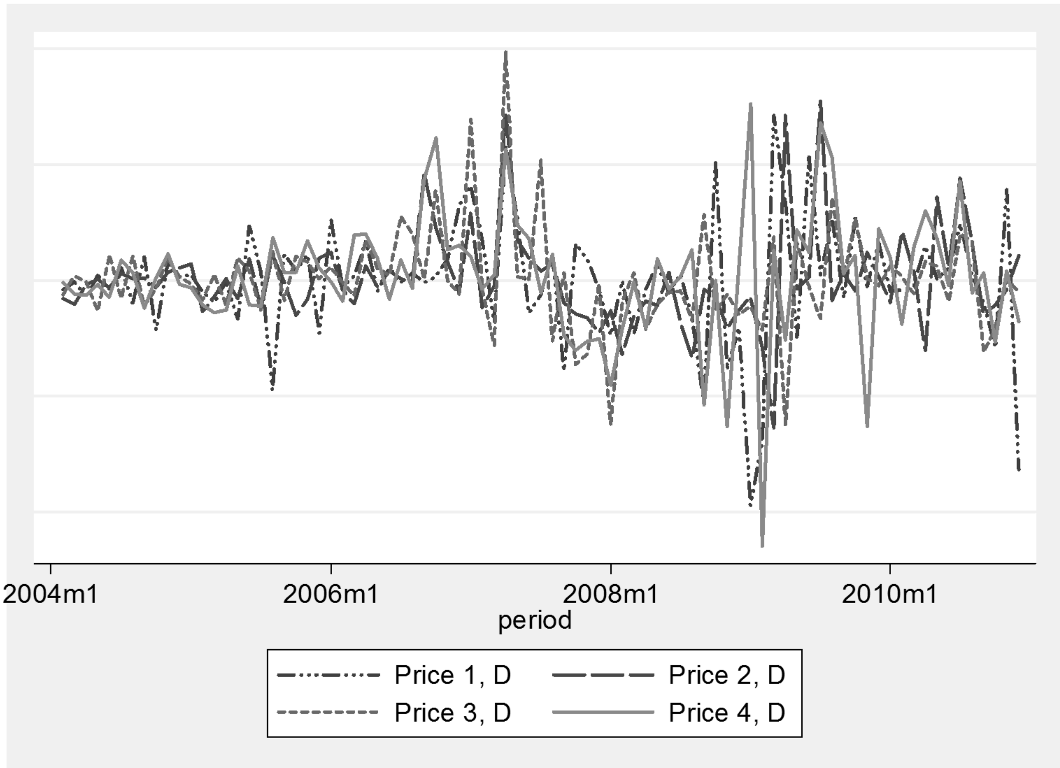


Figure 9. Plot of levels and first differences of real prices. Note that the y-axis is not the same for the different products as the data is highly sensitive for our case company.

7. Results

As Froeb and Werden (1999) already point out, the typical residual demand estimations do not usually take into account nonstationarity of the variables, and this is a major flaw in residual demand literature. With 2SLS or 3SLS, the typical methods used in the literature, taking nonstationarity of variables into account is generally not possible and as Granger and Newbold (1974) find, not taking into account stationarity leads to spurious regression and is against the assumptions of linear regressions.

Acknowledging this, we will still apply 2SLS in this study to see how the outcomes differ compared with Johansen's method that treats the variables as I(1). With Johansen's method, we are also able account for the dynamic features of the time series, which previously have been neglected in residual demand literature (Froeb and Werden, 1999).

7.1. Two Stage Least Squares Estimations

In 2SLS estimations we follow Baker and Bresnahan (1988) and use real prices in our estimations. For both center goods products, the estimated equation was of the following form:

$$p = \beta_0 + \beta_1 q + \beta_2 L.PPI_{saw} + \beta_3 L.SP + \beta_4 CP + \beta_5 Y + u,$$

where p is the real price for the good, q is the quantity sold of that good, PPI_{Saw} is the producer price index for sawmilling representing industry wide costs, SP is the real stumpage price for the wood type in question, CP is the number of construction permits in the current month and Y is the real GDP for Finland. L is a lag operator. For board products, product 3 and 4, also the respective fiberwood stumpage price was included in the regressions. For wood type A products, the regional stumpage price for wood type A logs in Kymi-Savo region was used to better capture the firm-specific costs.

In estimations for wood type B products, product 2 and 4, we use UPM's total production of wood type B as an instrument. For wood type A products, UPM's total production of all sawn wood was found to be a better instrument based on the postestimation tests.

For wood type B boards we use SEK/EUR exchange rate as an instrument, whereas for the other product groups, EUR/GBP was found to be a stronger instrument.

The results from the estimations can be seen in the tables below. The first stage estimations show that R-squared values and the F-statistic are high indicating that the instruments are strong. Minimum eigenvalue statistics presented in Appendix 2 pass the nominal 5% Wald test at 10% rejection rate further reinforcing the idea of strong instruments. Postestimation Sargan's tests for overidentifying restrictions confirm that the instruments are valid (see Appendix 2).

Table 6. Summary statistics from 1st stage regressions. The R-squared values and F tests are high.

|		Adjusted	Partial		
Variable |	**R-sq.**	**R-sq.**	**R-sq.**	**F(2,76)**	**Prob > F**
quantity 1 |	0.6631	0.6365	0.4255	28.1395	0.0000
quantity 2 |	0.6861	0.6613	0.3523	20.671	0.0000
quantity 3 |	0.6056	0.5687	0.3657	21.6198	0.0000
quantity 4 |	0.5556	0.5141	0.2890	15.2442	0.0000

Table 7. Second-stage regression results and summary statistics for center goods. The high R^2 would indicate that the model fits the data.

VARIABLES	price 1	VARIABLES	price 2
quantity 1	-0.0231*	**quantity 2**	-0.0123
	(0.0118)		(0.0126)
L.real_man_costs_saw	0.593**	**L.real_man_costs_saw**	0.355
	(0.263)		(0.267)
L.real_stumpagep_Alog	1.419**	**L.real_stumpagep_Blog**	0.733***
	(0.556)		(0.124)
L.real_stumpagep_Alog_ks	-0.960*	**fin_const_permits_quartal**	0.129***
	(0.533)		(0.0264)
fin_const_permits_quartal	0.135***	**fin_bkt**	-0.192
	(0.0217)		(0.188)
fin_bkt	0.0751	**Constant**	1.326
	(0.145)		(2.144)
Constant	-1.357		
	(1.673)		
Observations	83	**Observations**	83
R-squared	0.838	**R-squared**	0.798

Adj.R-Squared	0.825	**Adj.R-Squared**	0.784
RSS	0.204	**RSS**	0.283
F-Test	.	**F-Test**	.
Standard errors in parentheses			
***** p<0.01, ** p<0.05, * p<0.1**			

As can be seen in the table above, for both of the center good products the coefficient for quantity is not significantly different from zero at 10% significance level, i.e. the elasticity of residual is perfectly elastic. The prices are determined by costs and demand side variables. The signs of the coefficients are as expected: the industry-wide costs variables increase costs for all companies and the increased costs are then transferred into prices. Increased demand shown by an increase in the number of construction permits issued increases the prices. Rather surprisingly, the coefficient for real GDP is found insignificant.

Table 8. Second-stage regression results and summary statistics for boards. The regressions Cost-side factors remain significant; stumpage price of both logs and fiberwood together with PPI of saw milling explain most of the price movements. The high R^2 would indicate that the model fits the data.

VARIABLES	price 4	VARIABLES	price 3
quantity 4	-0.00226	**quantity 3**	-0.106***
	(0.0453)		(0.0385)
L.real_man_costs_saw	1.255***	**L.real_man_costs_saw**	2.132***
	(0.346)		(0.366)
L.real_stumpagep_Blog	0.918***	**L.real_stumpagep_Alog**	1.676***
	(0.174)		(0.583)
L.real_stumpagep_Bfiber	-0.775***	**L.real_stumpagep_Alog_ks**	-1.194**
	(0.128)		(0.535)
fin_const_permits_quartal	0.0859*	**L.real_stumpagep_Afiber**	-0.645***
	(0.0473)		(0.213)
fin_bkt	0.241	**fin_const_permits_quartal**	0.0347
	(0.224)		(0.0329)
Constant	-5.454**	**fin_bkt**	0.563***
	(2.420)		(0.197)
		Constant	-10.39***
			(2.279)
Observations	83	**Observations**	83
R-squared	0.775	**R-squared**	0.844
Adj.R-Squared	0.758	**Adj.R-Squared**	0.829
RSS	0.576	**RSS**	0.326
F-Test	.	**F-Test**	.

Standard errors in parentheses	
*** p<0.01, ** p<0.05, * p<0.1	

For board products all the cost side variables are found significant at 5% significance level and the signs of these costs are as previously: industry wide cost increases lead to an increase in price. Notice that the increase in the price of fiberwood leads to a decrease in price of boards. This supports the idea that fiberwood, acting as a proxy for woodchips, decreases the costs of production when its price increases. For product 4, the demand side variables are not significant at 5% level, although their signs are logical. Thus, only the costs determine the price of product 4. Surprisingly, for product 3 the real GDP is significant when for all the other products the coefficient is insignificant.

For product 4, the coefficient for own quantity is insignificant as expected. For product 3, the estimations show that UPM is able to earn small markups over marginal costs, the markup being 10%. Based on the correlation matrix presented in the data section, there should be no causality between the price and quantity of product 3 and this casts doubt on this result.

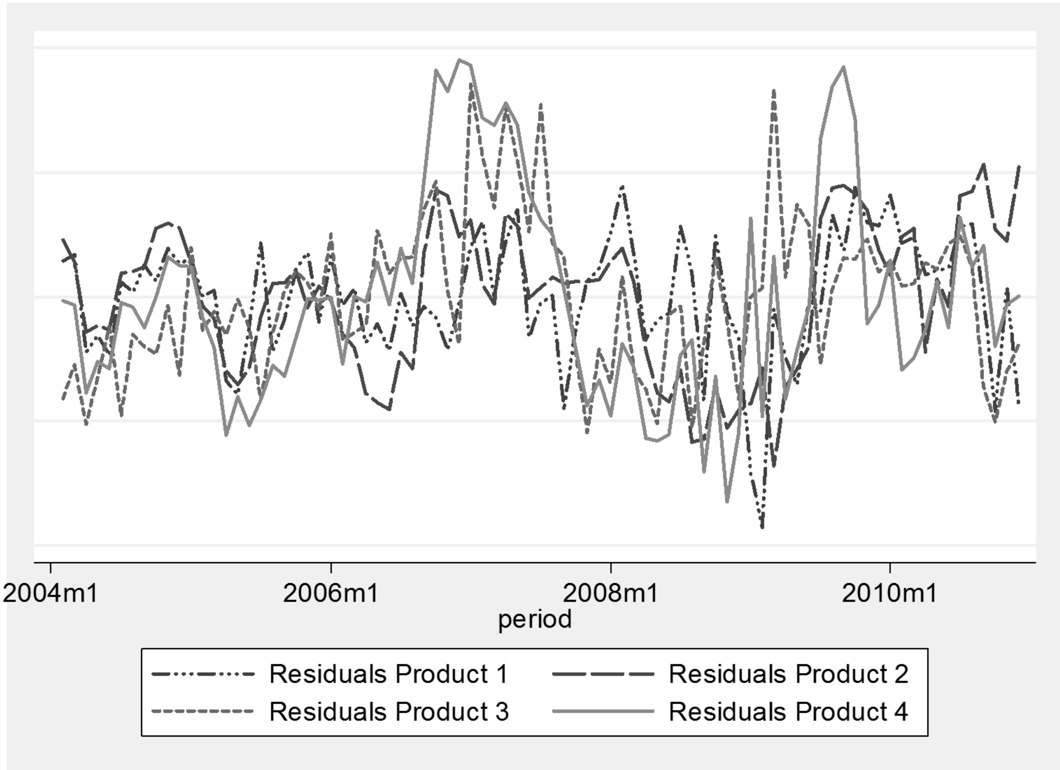


Figure 10. Plot of the 2SLS residuals. The residuals clearly do not follow a white noise process and show signs of autocorrelation.

To check for the validity of the results, the residuals are examined. From the residual plot in Figure 10 it is clear that the residuals are not IID. Also the Ljung-Box Q-tests for white noise (see Appendix 2) reject the null hypothesis of no autocorrelation. In other words, the test statistic shows that the residuals experience autocorrelation similar to Baker and Bresnahan (1988) findings and the results are not reliable.

To remove the autocorrelation, we introduce a lagged price term on the right hand side of the equation. This does indeed remove the autocorrelation in all estimations except for those for product 3 (see Appendix 3). The residual plot in Figure 11 shows that the residuals behave better in all the product groups than without the lagged price term. Removing the autocorrelation by adding a lagged variable on the RHS of the equation does not change the qualitative results for products 1, 2 and 4; the inverse elasticity of residual demand is still close to zero indicating that UPM's quantity decisions do not affect the prices it receives from the market. For product 3, this improved model removes the slight market power that the earlier estimations showed.

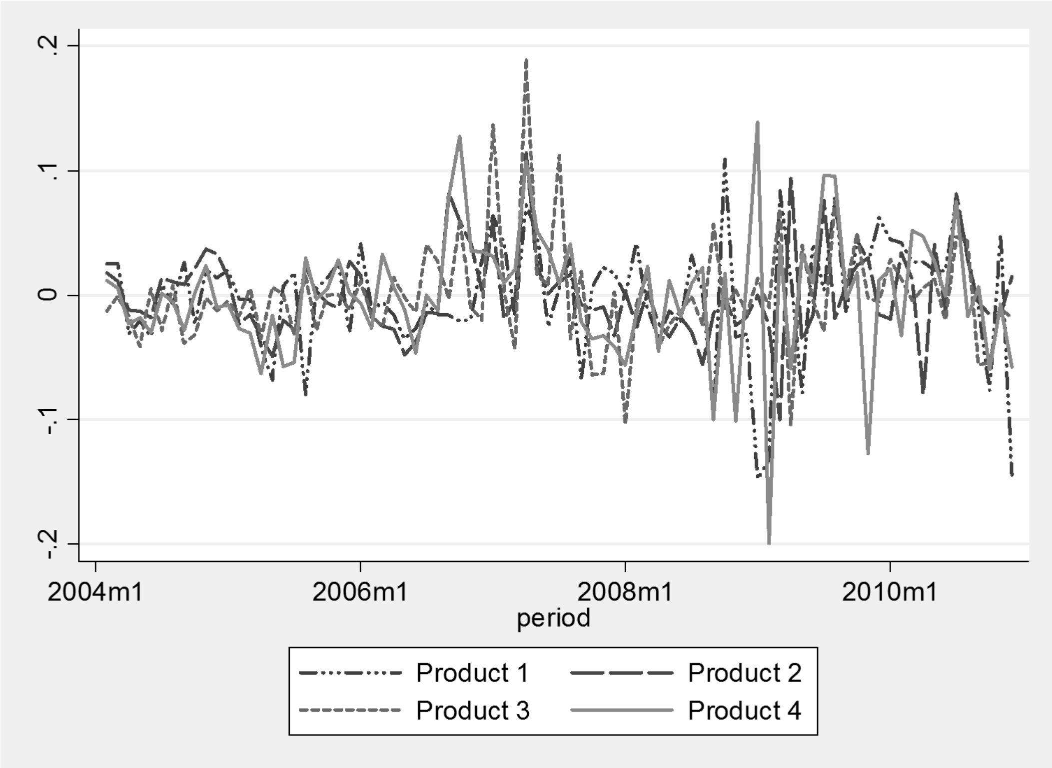


Figure 11. Plot of the 2SLS residuals when lagged price is introduced as a regressor. The residuals clearly do not follow a white noise process and show signs of autocorrelation.

The models in this section have strong and valid instruments and the residuals are quite well behaved. There is still one issue not addressed by these models: nonstationarity. However, it should be noted that the bias in spurious regressions is in the direction of rejecting a true null hypothesis (Grange and Newbold, 1974), i.e. finding a connection between series that in reality are independent. In these estimations, no connection was found and this should not be due to spurious regression problem. Thus, the results should not be affected even if the nonstationarity had been addressed properly.

Based on the 2SLS estimations UPM has no market power. To check for the robustness of these results, we will tackle the spurious regression problem next using a Vector Error Correction Model (VECM) that we described earlier.

7.2. Johansen's Method Estimations

The purpose of the VAR-estimations in this paper is to test the robustness of 2SLS results. The estimated VAR models do not include a trend term but do include a constant. The models are thus of the following form:

$$Dx_t = \gamma_0 + \alpha' ce_{t-1} + \sum_{i=1}^{k-1} \gamma_1 Dx_{t-i} + u_t,$$

where x_t is a vector containing the variables in the model, α is a vector including the adjustment parameters and its dimensions depend on the amount of CI vectors. The size of the adjustment parameter, as explained earlier, is interpreted as the speed of convergence towards equilibrium. Vector *ce* includes the lagged residual terms of the CI vectors. Parameter k is the amount of lags included in the model.

The variables included in x are

- Price and quantity sold of the specific wood type
- Nationwide stumpage price for the wood type in question
- Real GDP in Finland
- PPI for sawmilling

In addition, for board products (products 3 and 4) the stumpage price of fiberwood for that specific wood type is included in the model.

Lag length is chosen using information criteria. Tables of these statistics are provided in Appendix 4. When there was a conflict between different criteria, the lag length indicated by BIC was chosen. If Lagrange Multiplier test found autocorrelation in the postestimation tests, the lag length was increased as advised by Gonzalo (1994). Increasing the lag length removed the autocorrelation and the null hypotheses of no autocorrelation were not rejected at 5% in any of our models.

Ranks of the cointegrating matrices are then estimated using the optimal lag length. The rank of the matrix is chosen based on the trace and maximum eigenvalue statistics (see Appendix 4 for details). After this, the VECM is fitted. As we are mostly interested in the long-run equilibrium elasticities, the dynamics of the VECM are not shown and we focus only on the cointegrated vectors and the adjustment parameter vectors. The elasticity of residual demand is calculated based on the CI vectors and as the variables are in logarithms, the coefficients can again be interpreted as elasticities.

For both center-good products, one cointegrated vector is found in Johansen's tests and for product 3, the rank tests suggest two CI vectors. For product 4, the trace test and maximum eigenvalue test results conflict. The trace test rejects the existence of two CI vectors whereas the maximum eigenvalue test suggests that there would be two CI vectors. The results of the trace test are taken and the model is fitted assuming the relevant rank to be 1.

The CI vectors tha can be interpreted as demand equations are presented below. Note that the insignificant parameters are removed from the model.

$$P_{Product\ 1} = -0{,}06\ Q_{Product\ 1} + 0{,}96\ SP_{ALog} - 0{,}78\ PPI_{Saw} + 0{,}89\ Y \quad + error$$

$$P_{Product\ 2} = 5{,}58\ SP_{BLog} - 13{,}7\ PPI_{Saw} + 12{,}6\ Y \quad + error$$

$$P_{Product\ 3} = 0{,}53\ SP_{ALog} + 0{,}36\ SP_{AFiber} + 1{,}18\ PPI_{Saw} + 0{,}71\ Y \quad + error$$

$$P_{Product\ 4} = -0{,}24\ Q_{Product\ 4} + \ 2{,}00\ SP_{BLog} - 0{,}48\ SP_{BFiber} - 1{,}71\ \ Y \quad + error$$

For product 1, 2 and 3 the main results are similar to 2SLS estimations: the coefficients for the quantity variables (Q_i) are close to or exactly zero and the stumpage prices of logs are positively correlated with the prices of the products themselves. For products 1 and 2, the signs of production price index variable (PPI_{Saw}) are counterintuitive. The signs indicate that industry wide increase in costs would decrease the prices. For product 4 the coefficient for real GDP (Y) is also counterintuitive; an increase in demand through increased economic activity would decrease price.

For the dynamic equation for price, the adjustment coefficients (α) for the relevant CI vectors are small and the standard errors for the coefficients are high:

$$\alpha_{Product\ 1} = -0{,}05\ (Std. Err.\ 0{,}16)$$

$$\alpha_{Product\ 2} = -0{,}01\ (Std. Err.\ 0{,}17)$$

$$\alpha_{Product\ 3} = 0{,}13\ (Std. Err.\ 0{,}17)$$

$\alpha_{Product\ 4} = 0{,}10\ (Std.Err.\ 0{,}12)$

This means that price adjusts to the long-run equilibrium very slowly if at all.

The results give some support to the findings of 2SLS results: the inverse elasticity of residual demand is close to zero. For product 3, no market power is found and this conflicts with the results in 2SLS estimations with no lagged price variable but supports the findings in the improved model with lagged price variable on the right hand side. On the other hand, product 4 is found to have some market power with the Johansen's method, whereas with 2SLS, no connection between prices and quantities is found. If market power does exist in the long-run, it does not affect the dynamics of prices much as the alfa-coefficient is so small. As the correlation matrix already showed that there is no correlation in the prices and quantities for product 4 and the 2SLS estimations show no signs of causality, the whole existence of market power can be ruled out.

8. Conclusions

The current residual demand literature uses mainly two and three stage least squares (2SLS and 3SLS) methods in its estimations. With these methods, nonstationarity is an issue. Applying 2SLS or 3SLS methods to nonstationary time series can lead to spurious regressios. Still, as Froeb and Werden (1999) point out, residual demand literature has not taken this into account.

As Baker and Rubinfeld (1999) state, using statistical evidence has been a growing trend in US antitrust courts. If this trend is to continue, more emphasis should be put on the robustness of the estimations. The idea that results from potentially spurious regressions could have been used as statistical evidence in antitrust courts is frightening. This study expands the existing literature and offers a robustness check for the results of 2SLS estimations: a vector error correction model estimation using Johansen's method.

Already when analyzing UPM's sales data and the correlations between prices and quantities, it became clear that at least in the board product categories, products 3 and 4, UPM has no significant market power as the correlations between prices and quantities were practically zero. The 2SLS estimations supported this and the quantity coefficients were found close to or exactly zero for UPM for all product groups in 2SLS estimations.

The instrumental variable choices made in the 2SLS estimations were found relevant and valid, which further supports the findings. Still, the reliability of the results could have been further improved if more firm-specific cost data was available. For example, data on the prices at which UPM sells its woodchips, a significant by-product in sawn wood production, would have been an even more valid instrument.

Although our results from 2SLS estimations may be spurious, it should be noted that the bias in spurious regression estimators is in the direction of rejecting a true null hypothesis, the null hypothesis being that there is no connection between the two series at hand. In other words, spurious regressions find relationships between series that are in reality independent. As in our estimations no connections between the prices and quantities were found, i.e. the null hypothesis was not rejected, we may conclude that the results should not be affected even if the nonstationarity issues had been addressed properly.

Johansen's method mostly supported these findings as no significant market power was found for products 1, 2 or 3. Although some market power was found for product 4, this result can be ruled out as misspecification based on the results from the correlation matrix. If market power had been found in the 2SLS estimations, using Johansen's method would have been more informative in this study.

The results indicate that UPM's residual demand is perfectly elastic and a one-sided price increases by UPM will lead to severe decreases in demand making them unprofitable. Similarly, if UPM was to cut its quantity sold, the price would be left unaffected and UPM would experience smaller revenues. UPM should take the prices of sawn wood as given and focus only on optimizing the quantity it wants to supply at the current prices.

The results of this study are interesting and opposite to what we assumed before the actual estimations. As UPM is a large player in an industry that has a static market structure, it was thought to have at least some market power. To look for reasons for no market power, one has to look at the components that make up the elasticity of residual demand: the elasticity of market demand and the elasticity of supply of competitors (Landes and Posner, 1981). Here, a significant factor for the lack of market power is likely to be the elasticity of supply. As a large part of Finnish sawn wood production is exported, competitors can react to price increases in the domestic markets by increasing their domestic supply and selling less to export markets. Export markets are always secondary to domestic markets as the transportation costs for sawn wood are high.

Another reason for no market power can be price competition that will force the markups to zero. In theory, product differentiation should allow firms in price competition to have markups, and the products seem to be highly differentiated in the sawn wood industry. Still, this differentiation can be only superficial, as all the major players in Finland are able to produce the same products. Thus, price competition can be thought of as one reason for no markups and market power.

The sawn wood industry is an interesting industry for economic analysis as it has many sides to it. The raw material markets that greatly influence the sawn wood industry are already closely analyzed, but the industry's subordinate status relative to paper and pulp production and how this affects the motives and profit maximization could make for interesting research. As Kallio (2002) points out, there might be even overproduction in the field.

Another interesting topic for further research would be the price setting behavior in the field. As there is a clear oligopoly setup between Stora Enso, UPM and Metsäliitto, analyzing the dynamics of price setting in the field would be interesting. Based on our results, it seems that UPM is not the one setting the prices in the markets but Stora Enso as the biggest player could have a large influence on the markets.

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Appendix 1. Data

Plots of Data

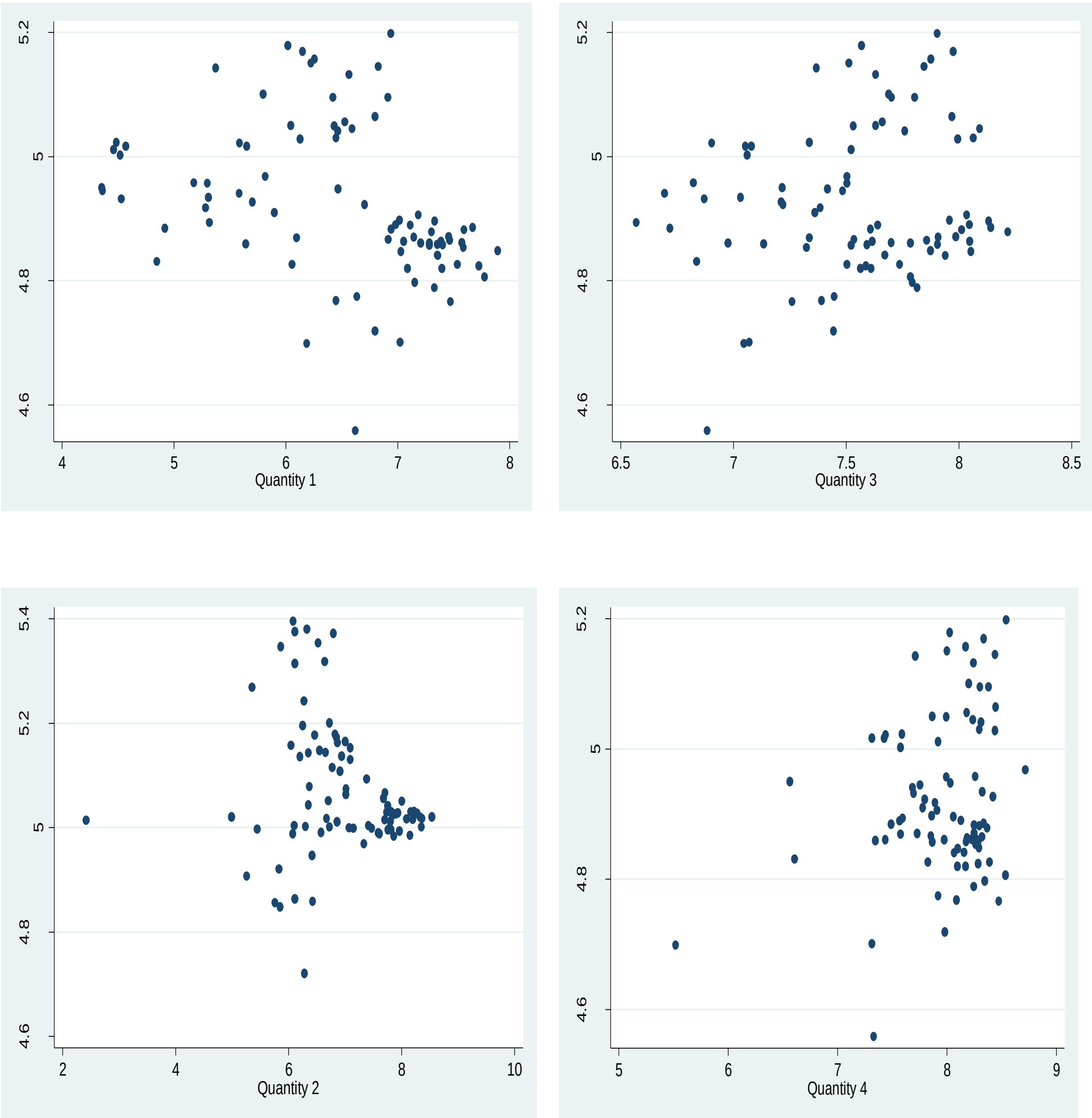
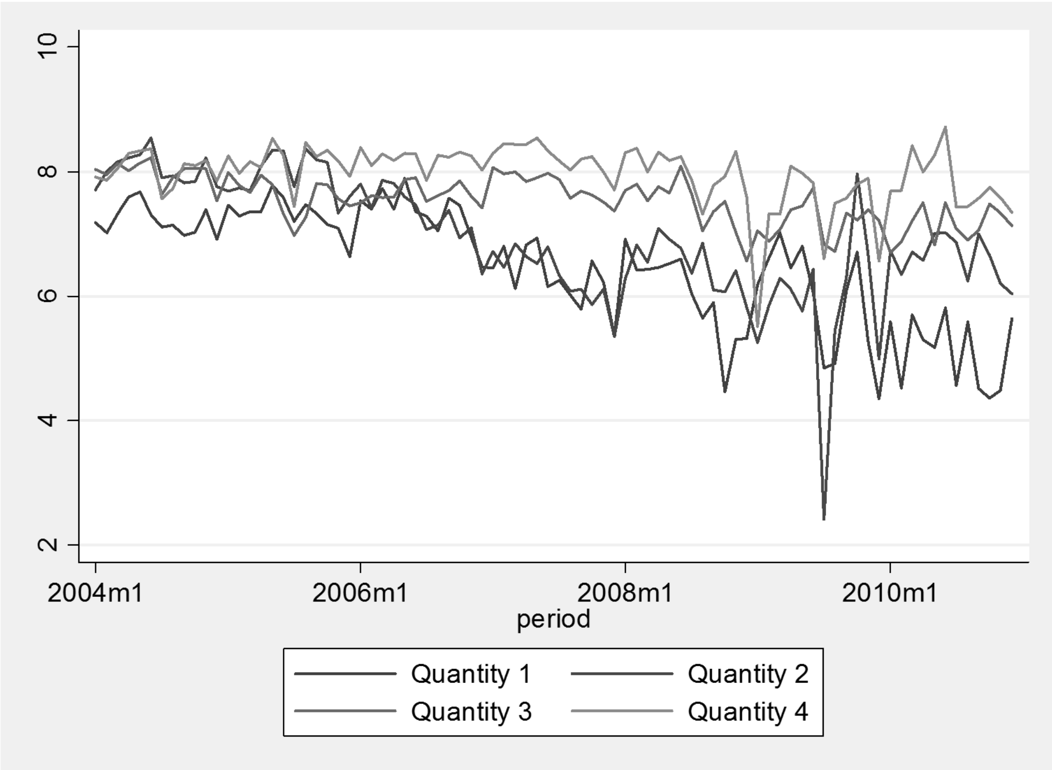


Figure 12. Scatter Plots of Quantity and Price



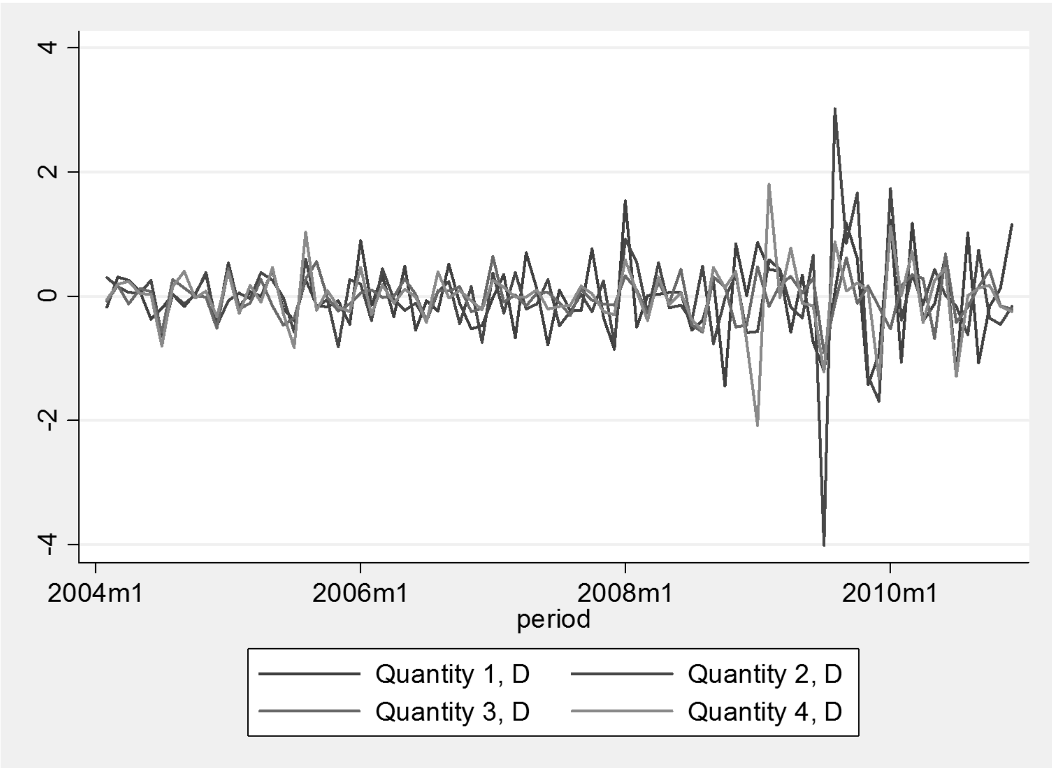


Figure 13. Plot of levels and first differences for quantities (m3) for different products. The y-axis is not the same for each line for privacy reasons. The levels seem to have a decreasing trend for all the products, but the differences seem to follow a white noise process.

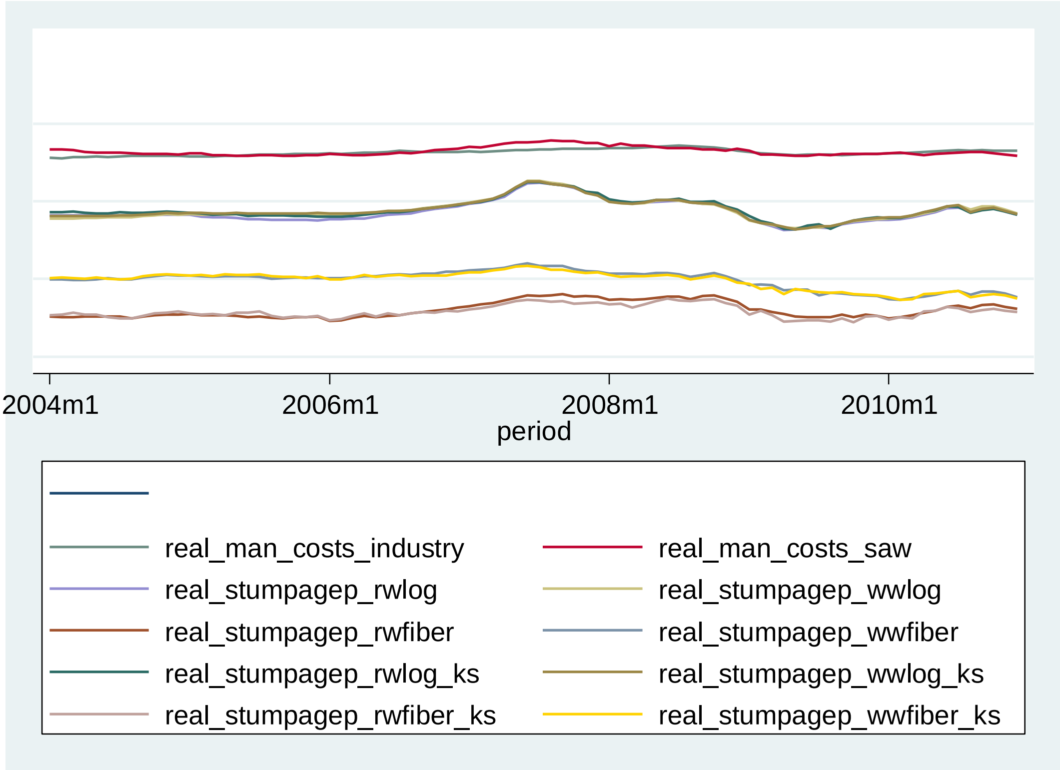


Figure 14. The real costs seem stationary in levels but DF tests show that they may be I(1)

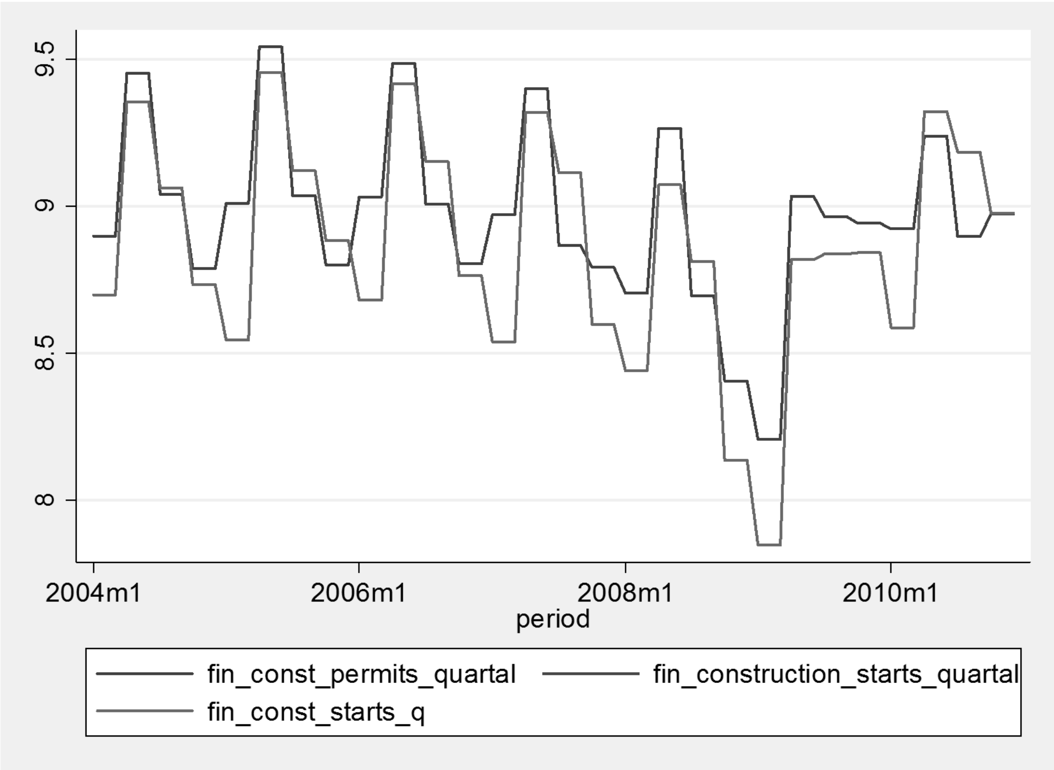


Figure 15. Construction permits and starts are extremely cyclical and there is a large peak on the 2nd quarter of the year. The data suffers from extrapolation as the monthly values are drawn from quarterly data.

Correlograms for Prices

```
                                                 -1       0       1 -1       0       1
 LAG        AC        PAC       Q      Prob>Q  [Autocorrelation]  [Partial Autocor]
-------------------------------------------------------------------------------
1         0.9026   0.9057   70.914  0.0000           |-------           |-------
2         0.8274   0.0334   131.22  0.0000           |------            |
3         0.7485  -0.0422    181.2  0.0000           |-----             |
4         0.6623  -0.1108    220.8  0.0000           |-----             |
5         0.5649  -0.1414   249.98  0.0000           |----             -|
6         0.4661  -0.0883    270.1  0.0000           |---               |
7         0.3629  -0.0971   282.45  0.0000           |--                |
8         0.2756   0.0318   289.67  0.0000           |--                |
9         0.1897  -0.0496   293.13  0.0000           |-                 |
10        0.1170   0.0383   294.47  0.0000           |                  |
```

Figure 16. Correlogram for real price of Product 1

```
                                                 -1       0       1 -1       0       1
```

```
 LAG       AC       PAC      Q     Prob>Q  [Autocorrelation]  [Partial Autocor]
-------------------------------------------------------------------------------
1        0.9431   0.9484   77.407  0.0000          |-------           |-------
2        0.8828  -0.0708   146.07  0.0000          |-------           |
3        0.8169  -0.0778   205.58  0.0000          |------            |
4        0.7171  -0.3474   252.01  0.0000          |-----           --|
5        0.6199   0.0002   287.15  0.0000          |----              |
6        0.5223  -0.0700   312.42  0.0000          |----              |
7        0.4273   0.0111   329.55  0.0000          |---               |
8        0.3110  -0.3772   338.74  0.0000          |--             ---|
9        0.2036  -0.0369   342.74  0.0000          |-                 |
10       0.1038   0.0203   343.79  0.0000          |                  |
```

Figure 17. Correlogram for real price of Product 2

```
                                          -1       0       1 -1       0       1
 LAG       AC       PAC      Q     Prob>Q  [Autocorrelation]  [Partial Autocor]
-------------------------------------------------------------------------------
1        0.9563   0.9572     79.6  0.0000          |-------           |-------
2        0.9235   0.1259   154.73  0.0000          |-------           |-
3        0.8842  -0.0808   224.46  0.0000          |-------           |
4        0.8050  -0.5789   282.97  0.0000          |------        ----|
5        0.7397  -0.0417   333.01  0.0000          |-----             |
6        0.6674   0.0248   374.26  0.0000          |-----             |
7        0.5830   0.1514   406.15  0.0000          |----              |-
8        0.5111   0.0091   430.98  0.0000          |----              |
9        0.4316  -0.1194   448.92  0.0000          |---               |
10       0.3533  -0.0950   461.11  0.0000          |--                |
```

Figure 18. Correlogram for real price of Product 3

```
                                          -1       0       1 -1       0       1
 LAG       AC       PAC      Q     Prob>Q  [Autocorrelation]  [Partial Autocor]
-------------------------------------------------------------------------------
1        0.9563   0.9572     79.6  0.0000          |-------           |-------
2        0.9235   0.1259   154.73  0.0000          |-------           |-
3        0.8842  -0.0808   224.46  0.0000          |-------           |
4        0.8050  -0.5789   282.97  0.0000          |------        ----|
5        0.7397  -0.0417   333.01  0.0000          |-----             |
6        0.6674   0.0248   374.26  0.0000          |-----             |
7        0.5830   0.1514   406.15  0.0000          |----              |-
8        0.5111   0.0091   430.98  0.0000          |----              |
9        0.4316  -0.1194   448.92  0.0000          |---               |
```

```
10       0.3533  -0.0950   461.11  0.0000         |--              |
```

Figure 19. Correlogram for real price of Product 4

ADF –Tests for Stationarity

The Dickey-Fuller test used was DF-GLS test where the ADF test equation is first turned into GLS before estimation. The results were calculated for lags 1-11, where the maximum lag was calculated with Schwert criterion and the optimal lag length was decided based on the two information criterion: Schwarz Bayesian Information Criterion and Akaike Information Criterion.

									Critical values	
Lag	Price 1	Price 2	Price 3	Price 4	D.Price 1	D.Price 2	D.Price 3	D.Price 4	1 %	5 %	10 %
11	-2.184	-2.500	-1.999	-2.452	**-1.479**	-1.933	-1.842	-1.781	-3.641	-2.745	-2.471
10	-2.211	-2.558	-1.807	-2.112	-1.794	-2.284	-1.948	-2.083	-3.641	-2.783	-2.508
9	-1.987	-2.522	-1.853	-2.272	-1.862	-2.270	-2.198	-2.462	-3.641	-2.822	-2.545
8	-2.152	-2.739	-1.739	-2.115	-2.225	-2.332	-2.215	-2.344	-3.641	-2.859	-2.581
7	-2.145	-2.829	-1.573	-2.338	-2.199	-2.168	-2.441	-2.590	-3.641	-2.896	-2.616
6	-2.313	-2.021	-1.620	-1.838	-2.367	**-2.100**	-2.808	**-2.403**	-3.641	-2.932	-2.649
5	-2.215	-2.127	-1.996	-1.879	-2.339	-3.003	-2.902	-3.224	-3.641	-2.966	-2.681
4	-2.118	-2.064	-2.136	-1.823	-2.615	-3.014	-2.503	-3.401	-3.641	-2.998	-2.710
3	-1.931	**-2.163**	**-2.158**	-2.031	-3.013	-3.282	-2.414	-3.858	-3.641	-3.027	-2.737
2	-1.785	-1.527	-1.097	-1.827	-3.824	**-3.329**	**-2.471**	-3.789	-3.641	-3.054	-2.762
1	**-1.778**	**-1.442**	-1.017	**-1.513**	**-5.268**	-5.470	-5.766	**-4.848**	-3.641	-3.077	-2.783
SC	1	3	3	1	1	2	2	1			
MAIC	1	1	3	1	11	6	2	6			

Figure 20. ADF tests with different lags for different lags for prices. The bolded figures are those suggested by information criteria. All price series seem difference stationary

					Critical values	
	D.Quantity 1	D.Quantity 2	D.Quantity 3	D.Quantity 4	1 %	5 %	10 %
11	**-1.203**	**-1.957**	-2.568	-2.730	-3.645	-2.742	-2.468
10	-1.351	-2.040	-3.579	-3.053	-3.645	-2.781	-2.506
9	-1.603	-2.193	-3.215	-3.192	-3.645	-2.820	-2.543
8	-1.863	-2.405	-2.795	-2.844	-3.645	-2.858	-2.580
7	-2.311	-2.572	-3.069	-3.428	-3.645	-2.896	-2.616
6	-3.053	-3.181	-3.721	-3.907	-3.645	-2.932	-2.650
5	-3.407	-4.208	-4.889	-5.278	-3.645	-2.967	-2.682
4	-3.718	-4.608	-5.064	-6.119	-3.645	-2.999	-2.712

3	-4.628	-6.628	-6.260	**-8.479**	-3.645	-3.029	-2.739
2	-5.420	**-7.539**	-7.714	-8.074	-3.645	-3.056	-2.764
1	**-7.099**	-8.051	**-9.533**	**-8.460**	-3.645	-3.080	-2.785
SC	1	2	1	3			
MAIC	11	11	1	1			

Figure 21. ADF tests with different lags for quantities. The series are difference stationary based on Schwarz Bayesian Information Criterion (SC) but MAIC shows conflicting results.

										Critical value		
	D.PPI sawing	D.ks_~_Alog	D.fin_~_Alog	D.fin_~_Blog	D.real_~Alog	D.real_~Blog	D.real_s~Afiber	D.real_s~Bfiber	D.real_~Alog_ks	1 %	5 %	10 %
11	-1.916	**-1.464**	-1.526	-1.686	-1.505	-1.697	-1.826	-2.214	**-1.435**	-3.641	-2.745	-2.471
10	-1.642	-2.025	-1.933	-1.928	-1.929	-1.923	-2.103	-2.570	-2.042	-3.641	-2.783	-2.508
9	-1.882	-2.849	-2.361	-2.294	-2.225	-2.183	-2.107	-2.819	-2.699	-3.641	-2.822	-2.545
8	-2.113	-2.645	-2.540	-2.606	-2.530	-2.593	-2.623	-2.891	-2.658	-3.641	-2.859	-2.581
7	-1.934	-3.381	-2.917	-2.885	-2.916	-2.861	-3.088	-2.795	-3.361	-3.641	-2.896	-2.616
6	-1.965	-3.267	-3.153	-3.469	-3.023	-3.342	-2.623	-2.619	-3.187	-3.641	-2.932	-2.649
5	-1.857	-2.999	-3.050	-3.172	-3.041	-3.198	-2.729	**-2.546**	-2.964	-3.641	-2.966	-2.681
4	-2.195	-2.913	-3.298	-3.529	-3.380	-3.474	**-2.587**	-2.959	-2.937	-3.641	-2.998	-2.710
3	-2.515	-3.115	-3.073	-3.105	-2.904	-3.044	-2.858	-3.239	-3.026	-3.641	-3.027	-2.737
2	**-3.298**	-2.860	**-2.535**	**-2.855**	**-2.662**	**-2.926**	-3.178	**-3.528**	-2.911	-3.641	-3.054	-2.762
1	-4.492	**-4.074**	-3.582	**-3.491**	**-3.397**	**-3.354**	**-4.342**	-5.811	**-3.935**	-3.641	-3.077	-2.783
SC	2	1	2	1	1	1	1	2	1			
MAIC	2	11	2	2	2	2	4	5	11			

Figure 22. ADF tests with different lags for cost side variables. Based on SC all series are difference stationary.

				Critical value		
	D.GDP	const_permits	D.const_permits	1 %	5 %	10 %
11	-1.138	-1.055	-1.977	-3.641	-2.745	-2.471
10	-3.911	-1.052	-4.709	-3.641	-2.783	-2.508
9	-4.500	-1.049	-5.975	-3.641	-2.822	-2.545
8	-5.480	-2.747	-9.301	-3.641	-2.859	-2.581
7	-3.153	-2.611	-4.165	-3.641	-2.896	-2.616
6	-3.443	-2.497	-4.881	-3.641	-2.932	-2.649
5	-3.826	-4.067	-6.110	-3.641	-2.966	-2.681
4	-5.077	-3.666	-4.126	-3.641	-2.998	-2.710
3	-6.432	-3.372	-4.827	-3.641	-3.027	-2.737
2	-10.147	-4.008	-6.023	-3.641	-3.054	-2.762
1	-6.201	-3.647	**-5.917**	-3.641	-3.077	-2.783

SC	9	11	9	
MAIC	9	9	1	

Figure 23. ADF tests with different lags for demand side variables. Based on SC all series are difference stationary.

Appendix 2. 2SLS Outputs

```
. //================= Product 1 =======================
```

First-stage regressions

```
----------------------

                                                Number of obs   =         83
                                                F(   7,     75) =      23.15
                                                Prob > F        =     0.0000
                                                R-squared       =     0.6836
                                                Adj R-squared   =     0.6540
                                                Root MSE        =     0.5638

------------------------------------------------------------------------------
quantity 1   |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
real_man_c~w |
         L1. |   7.311325   3.065089     2.39   0.020     1.205355     13.4173
             |
real_s~Alog |
         L1. |  -15.07522   5.289865    -2.85   0.006    -25.61317    -4.53727
             |
rea~Alog_ks |
         L1. |    10.4327   5.255406     1.99   0.051    -.0366066    20.90201
             |
fin_const_~l |   .0744463   .2431461     0.31   0.760    -.4099255    .5588181
     fin_bkt |  -.3582646    1.63092    -0.22   0.827    -3.607225    2.890696
     ln_prod |   .1479721   .1849057     0.80   0.426    -.2203789     .516323
         gbp |   -5.74854   .8601022    -6.68   0.000    -7.461951   -4.035128
       _cons |  -10.47564   19.28449    -0.54   0.589    -48.89231    27.94103
------------------------------------------------------------------------------
```

Instrumental variables (2SLS) regression

```
                                                   Number of obs =      83
                                                    Wald chi2(6)  =  412.83
                                                    Prob > chi2   =  0.0000
                                                    R-squared     =  0.8382
                                                    Root MSE      =  .04962

------------------------------------------------------------------------------
 price 1     |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
fin_Ac_q~1   |  -.0230783   .0118252    -1.95   0.051    -.0462553    .0000986
             |
real_man_c~w |
         L1. |   .5930955   .2629189     2.26   0.024     .0777839    1.108407
             |
real_s~Alog |
         L1. |   1.419117   .5558302     2.55   0.011     .3297096    2.508524
             |
rea~Alog_ks |
         L1. |   -.960133   .5332896    -1.80   0.072    -2.005361    .0850954
             |
fin_const_~l |   .1349977   .0217061     6.22   0.000     .0924545    .1775408
     fin_bkt |    .075066   .1445864     0.52   0.604    -.2083181    .3584501
```

```
       _cons |  -1.356753   1.672848    -0.81   0.417    -4.635474    1.921968
------------------------------------------------------------------------------
```

. //================== **Product 2** ========================

First-stage regressions

```
-----------------------

                                                Number of obs   =         83
                                                F(   6,     76) =      25.49
                                                Prob > F        =     0.0000
                                                R-squared       =     0.6680
                                                Adj R-squared   =     0.6418
                                                Root MSE        =     0.5902

------------------------------------------------------------------------------
quantity 2   |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
real_man_c~w |
         L1. |  -6.752262   2.494633    -2.71   0.008    -11.72075    -1.78377
             |
real_s~Blog |
         L1. |    .384768   1.303988     0.30   0.769    -2.212349    2.981885
             |
fin_const_~l |   .3746891   .2498342     1.50   0.138    -.1228988     .872277
     fin_bkt |  -2.714606    1.79643    -1.51   0.135    -6.292507    .8632946
  ln_prod_B |   .8988047   .1669396     5.38   0.000     .5663156    1.231294
         gbp |   -2.76474   .8348386    -3.31   0.001    -4.427466   -1.102015
       _cons |   48.69835   18.82995     2.59   0.012     11.19526    86.20145
------------------------------------------------------------------------------
```

Instrumental variables (2SLS) regression

```
                                                   Number of obs =      83
                                                    Wald chi2(5)   =  323.65
                                                    Prob > chi2    =  0.0000
                                                    R-squared      =  0.7975
                                                    Root MSE       =  .05839

------------------------------------------------------------------------------
 price 2 |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
fin_Bc_4~3   |  -.0123168   .0126261    -0.98   0.329    -.0370635    .0124299
             |
real_man_c~w |
         L1. |   .3545382   .2667805     1.33   0.184     -.168342    .8774184
             |
real_s~Blog |
         L1. |   .7325875   .1235806     5.93   0.000      .490374    .9748011
             |
fin_const_~l |   .1288891   .0263611     4.89   0.000     .0772224    .1805559
     fin_bkt |  -.1922062    .188389    -1.02   0.308    -.5614418    .1770294
       _cons |   1.325886   2.144101     0.62   0.536    -2.876475    5.528247
------------------------------------------------------------------------------
```

```
. //================= Product 3 =====================
```

First-stage regressions

```
-----------------------

                                                  Number of obs   =         83
                                                  F(   8,     74) =      15.62
                                                  Prob > F        =     0.0000
                                                  R-squared       =     0.6281
                                                  Adj R-squared   =     0.5879
                                                  Root MSE        =     0.2500

------------------------------------------------------------------------------
price 3      |      Coef.   Std. Err.      t    P>|t|     [95%
Conf. Interval]
-------------+----------------------------------------------------------------
real_man_c~w |
         L1. |   2.921611   1.409057     2.07  0.042     .1140041    5.729217
             |
real_s~Alog  |
         L1. |   2.484093    2.37581     1.05   0.299    -2.249812    7.217998
             |
rea~Alog_ks  |
         L1. |  -4.312253   2.331841    -1.85   0.068    -8.958548    .3340425
             |
real~Afiber |
         L1. |   1.214746   .9394751     1.29   0.200    -.6571993    3.086691
             |
fin_const_~l |  .3167015    .1134855     2.79   0.007     .0905768    .5428263
     fin_bkt |  -.7796894    .776625    -1.00   0.319    -2.327149    .7677698
     ln_prod |    .142773   .0828185     1.72   0.089    -.0222465    .3077924
         gbp |   -2.52433   .4402783    -5.73   0.000    -3.401603   -1.647056
       _cons |   .1204325   9.124526     0.01   0.990    -18.06058    18.30145
------------------------------------------------------------------------------
```

Instrumental variables (2SLS) regression

```
                                                     Number of obs =      83
                                                      Wald chi2(7)   =  448.96
                                                      Prob > chi2    =  0.0000
                                                      R-squared      =  0.8440
                                                      Root MSE       =  .06269

------------------------------------------------------------------------------
 price 3 |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
fin_Ab_6~3   |  -.1060776   .0385319    -2.75   0.006    -.1815988   -.0305563
             |
real_man_c~w |
         L1. |   2.131729   .3664718     5.82   0.000     1.413457        2.85
             |
real_s~Alog  |
         L1. |   1.675598   .5830885     2.87   0.004     .5327659    2.818431
             |
rea~Alog_ks  |
         L1. |  -1.193512   .5347726    -2.23   0.026    -2.241647   -.1453774
             |
```

```
real~Afiber  |
         L1. |  -.6447715    .212782    -3.03   0.002    -1.061817   -.2277265
             |
fin_const_~l |    .034675   .0328511     1.06   0.291     -.029712    .0990619
     fin_bkt |   .5632416    .196835     2.86   0.004     .1774521    .9490311
       _cons |  -10.39102   2.278622    -4.56   0.000    -14.85704   -5.925005
------------------------------------------------------------------------------
```

First-stage regression summary statistics

```
  --------------------------------------------------------------------------
               |            Adjusted      Partial
      Variable |   R-sq.       R-sq.        R-sq.      F(2,74)   Prob > F
  -------------+------------------------------------------------------------
  fin_Ab_6~3   |  0.6281      0.5879       0.3639      21.1682    0.0000
  --------------------------------------------------------------------------
```

. //================== **Product 4** ========================

First-stage regressions

```
-----------------------

                                                  Number of obs   =         83
                                                  F(   7,     75) =      13.39
                                                  Prob > F        =     0.0000
                                                  R-squared       =     0.5555
                                                  Adj R-squared   =     0.5140
                                                  Root MSE        =     0.3370

------------------------------------------------------------------------------
fin_Bb_6~3   |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
real_man_c~w |
         L1. |   -.757646   1.497139    -0.51   0.614    -3.740099    2.224807
             |
real_s~Blog  |
         L1. |  -.1151047   .8017102    -0.14   0.886    -1.712193    1.481984
             |
real~Bfiber  |
         L1. |   .8809104   .4653348     1.89   0.062    -.0460839    1.807905
             |
fin_const_~l |    .560717   .1490482     3.76   0.000     .2637977    .8576363
     fin_bkt |   1.426089   .9657021     1.48   0.144    -.4976883    3.349866
  ln_prod_B  |   .4838348   .0987007     4.90   0.000     .2872128    .6804568
         sek |  -.3443261   1.127766    -0.31   0.761    -2.590951    1.902299
       _cons |  -13.66809   10.11207    -1.35   0.181    -33.81236    6.476183
------------------------------------------------------------------------------
```

Instrumental variables (2SLS) regression

```
Number of obs =      83
 Wald chi2(6)   =  286.32
 Prob > chi2    =  0.0000
 R-squared      =  0.7754
 Root MSE       =  .08328
```

```
------------------------------------------------------------------------------
price 4      |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
fin_Bb_6~3   |  -.0022627    .045267    -0.05   0.960    -.0909844    .0864591
             |
real_man_c~w |
         L1. |   1.255416    .346274     3.63   0.000     .5767314    1.934101
             |
real_s~Blog  |
         L1. |   .9177936    .173673     5.28   0.000     .5774008    1.258186
             |
real~Bfiber  |
         L1. |  -.7749727   .1283053    -6.04   0.000    -1.026446    -.523499
             |
fin_const_~l |   .0859443   .0473208     1.82   0.069    -.0068028    .1786914
     fin_bkt |   .2410355   .2241285     1.08   0.282    -.1982483    .6803193
       _cons |  -5.453625   2.420185    -2.25   0.024     -10.1971   -.7101494
------------------------------------------------------------------------------
```

Postestimation Tests

Results for minimum eigenvalue statistics

Dependent Variable in the 2SLS Estimation	Minimum Eigenvalue Statistic			
Product 1	27.6952			
Product 2	30.6963			
Product 3	21.1682			
Product 4	14.8979			
	10%	15%	20%	30%
Nominal 5% Wald test critical values	19.93	11.59	4.42	3.92

Tests of overidentifying restrictions

Dependent Variable in the 2SLS Estimation	Sargan (score) chi2(1)
Product 1	.000376 (p = 0.9845)
Product 2	.284638 (p = 0.5937)
Product 3	.029923 (p = 0.8627)
Product 4	.63301 (p = 0.4263)

Here are the results for Ljung-Box Q-tests for no autocorrelation

Dependent Variable in 2SLS estimations	Portmanteau (Q) statistic	Prob > chi2(12)
Product 1	40.1315	0.0001
Product 2	110.0361	0.0000
Product 3	66.5416	0.0000
Product 4	145.0022	0.0000

Appendix 3. 2SLS Outputs with Lagged Price on RHS

```
. //================== Product 1 ========================
Instrumental variables (2SLS) regression             Number of obs =      83
                                                     Wald chi2(7)  =  484.67
                                                     Prob > chi2   =  0.0000
                                                     R-squared     =  0.8532
                                                     Root MSE      =  .04725

------------------------------------------------------------------------------
 price 1     |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
fin_Ac_q~1   |   .0033144   .0151222     0.22   0.827    -.0263245    .0329534
             |
    price 1  |
        L1.  |   .5959535   .1456131     4.09   0.000      .310557    .8813499
             |
real_man_c~w |
        L1.  |   .2167066   .2729701     0.79   0.427     -.318305    .7517183
             |
real_s~Alog  |
        L1.  |   1.019431   .5127607     1.99   0.047     .0144387    2.024424
             |
rea~Alog_ks  |
        L1.  |  -.8876645   .5033851    -1.76   0.078    -1.874281    .0989522
             |
fin_const_~l |   .0694731   .0285228     2.44   0.015     .0135695    .1253768
     fin_bkt |    .161347   .1420889     1.14   0.256    -.1171421     .439836
       _cons |  -1.679305   1.599093    -1.05   0.294    -4.813469     1.45486
------------------------------------------------------------------------------

  First-stage regression summary statistics
  ---------------------------------------------------------------------------
               |            Adjusted      Partial
      Variable |   R-sq.       R-sq.        R-sq.       F(2,74)   Prob > F
  -------------+-------------------------------------------------------------
  fin_Ac_30~3 |  0.7321      0.7031       0.3261       17.9016    0.0000
  ---------------------------------------------------------------------------

. //================== Product 2 ========================
Instrumental variables (2SLS) regression             Number of obs =      83
                                                     Wald chi2(6)  = 1029.85
                                                     Prob > chi2   =  0.0000
                                                     R-squared     =  0.9261
                                                     Root MSE      =  .03526

------------------------------------------------------------------------------
 price 2     |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
fin_Bc_q~2   |  -.0154625   .0076339    -2.03   0.043    -.0304247   -.0005003
             |
    price 2  |
        L1.  |   .8388245   .0701231    11.96   0.000     .7013858    .9762631
             |
real_man_c~w |
        L1.  |  -.1726402    .167306    -1.03   0.302    -.5005539    .1552735
```

```
             |
real_s~Blog  |
         L1. |   .1776885   .0876217     2.03   0.043     .0059532    .3494238
             |
fin_const_~l |   .0766851   .0164789     4.65   0.000      .044387    .1089831
     fin_bkt |  -.0776432   .1141045    -0.68   0.496    -.3012838    .1459975
       _cons |   1.084262   1.294951     0.84   0.402    -1.453796    3.622321
------------------------------------------------------------------------------

  First-stage regression summary statistics
  --------------------------------------------------------------------------
             |            Adjusted      Partial
    Variable |   R-sq.       R-sq.        R-sq.       F(2,75)   Prob > F
  -------------+------------------------------------------------------------
  fin_Bc_q¨2   |  0.6681      0.6371       0.4463       30.2323    0.0000
  --------------------------------------------------------------------------
```

. //================== Product 3 ========================

```
Instrumental variables (2SLS) regression               Number of obs =      83
                                                       Wald chi2(8)  = 1047.29
                                                       Prob > chi2   =  0.0000
                                                       R-squared     =  0.9265
                                                       Root MSE      =  .04302

------------------------------------------------------------------------------
 price 3     |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
fin_Ab_q~3   |   .0059821   .0332774     0.18   0.857    -.0592405    .0712047
             |
    price 3  |
         L1. |    .900003   .1112751     8.09   0.000     .6819078    1.118098
             |
real_man_c~w |
         L1. |   .0798236   .3756126     0.21   0.832    -.6563636    .8160109
             |
real_s~Alog  |
         L1. |   .2503862   .4349563     0.58   0.565    -.6021126    1.102885
             |
rea~Alog_ks |
         L1. |  -.1433267   .3841735    -0.37   0.709    -.8962929    .6096396
             |
real~Afiber |
         L1. |  -.1873891   .1627269    -1.15   0.250    -.5063279    .1315498
             |
fin_const_~l |   .0034186    .023456     0.15   0.884    -.0425544    .0493916
     fin_bkt |   .1848156   .1407279     1.31   0.189     -.091006    .4606372
       _cons |  -1.668366   1.913271    -0.87   0.383    -5.418308    2.081576
------------------------------------------------------------------------------

  First-stage regression summary statistics
  --------------------------------------------------------------------------
             |            Adjusted      Partial
    Variable |   R-sq.       R-sq.        R-sq.       F(2,73)   Prob > F
  -------------+------------------------------------------------------------
  fin_Ab_6~3  |  0.6482      0.6048       0.2764       13.9408    0.0000
  --------------------------------------------------------------------------
```

```
. //================== Product 4 ========================

Instrumental variables (2SLS) regression          Number of obs =      83
                                                  Wald chi2(7)  =  884.92
                                                  Prob > chi2   =  0.0000
                                                  R-squared     =  0.9149
                                                  Root MSE      =  .05127

------------------------------------------------------------------------------
price 4      |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
fin_Bb_q~4   |  -.0231331   .0282648    -0.82   0.413     -.078531    .0322648
             |
    price 4  |
         L1. |   .9806031   .0875376    11.20   0.000     .8090326    1.152174
             |
real_man_c~w |
         L1. |  -.2016753   .2531914    -0.80   0.426    -.6979214    .2945707
             |
real_s~Blog  |
         L1. |   .0171817   .1318825     0.13   0.896    -.2413032    .2756666
             |
real~Bfiber  |
         L1. |    .037542   .1121887     0.33   0.738    -.1823439    .2574279
             |
fin_const_~l |    .047064   .0288708     1.63   0.103    -.0095218    .1036497
     fin_bkt |   .0785296   .1387076     0.57   0.571    -.1933324    .3503915
       _cons |  -.1314181   1.563516    -0.08   0.933    -3.195853    2.933017
------------------------------------------------------------------------------

  First-stage regression summary statistics
  --------------------------------------------------------------------------
               |            Adjusted      Partial
      Variable |   R-sq.       R-sq.        R-sq.       F(2,74)   Prob > F
  -------------+------------------------------------------------------------
  fin_Bb_q~4   |  0.5617      0.5144       0.2815       14.4944    0.0000
  --------------------------------------------------------------------------
```

Postestimation Tests

Results for minimum eigenvalue statistics

Dependent Variable in the 2SLS Estimation	Minimum Eigenvalue Statistic			
Product 1	17.9016			
Product 2	30.2323			
Product 3	13.9408			
Product 4	14.4944			
	10%	15%	20%	30%
Nominal 5% Wald test critical values	19.93	11.59	4.42	3.92

Tests of overidentifying restrictions

Dependent Variable in the 2SLS Estimation	Sargan (score) chi2(1)
Product 1	.009126 (p = 0.9239)
Product 2	2.69132 (p = 0.1009)
Product 3	.360599 (p = 0.5482)
Product 4	.077433 (p = 0.7808)

Table 9. Ljung-Box tests for no autocorrelation

Dependent Variable in 2SLS estimations	Portmanteau (Q) statistic	Prob > chi2(12)
Product 1	6.7413	0.8742
Product 2	11.5054	0.4862
Product 3	31.6010	0.0016
Product 4	12.9972	0.3692

Appendix 4. Estimations with Johansen's Method

Choosing Lag Length and Rank

Table 10. Choosing Lag for product 1.

Selection-order criteria
Sample: 2004m5 - 2010m12 Number of obs = 80

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	382.414				5.5e-11	-9.43534	-9.37565	-9.28646
1	666.283	567.74	25	0.000	8.5e-14	-15.9071	-15.549	-15.0138*
2	706.903	81.24	25	0.000	5.8e-14	-16.2976	-15.641	-14.6599
3	740.263	66.719	25	0.000	4.8e-14	-16.5066	-15.5515	-14.1245
4	783.821	87.116*	25	0.000	3.1e-14*	-16.9705*	-15.717*	-13.8441

Table 11. Choosing Lag for product 2.

Selection-order criteria
Sample: 2004m5 - 2010m12 Number of obs = 80

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	377.99				6.1e-11	-9.32475	-9.26506	-9.17587
1	668.115	580.25	25	0.000	8.1e-14	-15.9529	-15.5947	-15.0596*
2	720.721	105.21	25	0.000	4.1e-14	-16.643	-15.9865	-15.0054
3	753.346	65.249	25	0.000	3.5e-14	-16.8336	-15.8786	-14.4516
4	799.581	92.471*	25	0.000	2.1e-14*	-17.3645*	-16.1111*	-14.2381

Table 12. Choosing Lag for product 3.

Selection-order criteria
Sample: 2004m5 - 2010m12 Number of obs = 80

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	618.471				9.0e-15	-15.3118	-15.2402	-15.1331
1	965.771	694.6	36	0.000	3.8e-18	-23.0943	-22.5929	-21.8437*
2	1014.43	97.32	36	0.000	2.8e-18	-23.4108	-22.4796	-21.0883
3	1068.03	107.2	36	0.000	1.9e-18	-23.8508	-22.4898	-20.4564
4	1136.93	137.81*	36	0.000	8.8e-19*	-24.6734*	-22.8827*	-20.2071

Table 13. Choosing Lag for product 4.

Selection-order criteria
Sample: 2004m5 - 2010m12 Number of obs = 80

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	500.206				1.7e-13	-12.3552	-12.2835	-12.1765
1	936.256	872.1	36	0.000	7.9e-18	-22.3564	-21.855	-21.1058*

```
|  2 |  995.073  117.63   36  0.000  4.5e-18  -22.9268  -21.9957* -20.6043  |
|  3 |  1042.32  94.498   36  0.000  3.5e-18*  -23.208  -21.8471  -19.8137  |
|  4 |  1080.54  76.428*  36  0.000  3.6e-18  -23.2634* -21.4727  -18.7971  |
+-------------------------------------------------------------------------+
```

Trace and Maximum eigenvalue tests for Rank

		rank	parms	LL	eigenvalue	trace stat	value
Product 1	Trace	1	9	669.64902	0.39323	29.3533*	39.89
	Max	1	9	669.64902	0.39323	20.4502	23.80
Product 2	Trace	1	9	666.02261	0.36533	32.8582*	39.89
	Max	1	9	666.02261	0.36533	19.2662	23.80
Product 3	Trace	2	128	1110.8936	0.42712	37.6436*	39.89
	Max	2	128	1110.8936	0.42712	20.3706	23.80
Product 4	Trace	1	11	934.56362	0.63608	53.6770*	59.46
	Max	2	20	950.25494	0.31484	16.1854	23.80

Fitting the VECM

Table 14. CI vector and Adjustment parameters for Product 1

```
Cointegrating equations

------------------------------------------------------------------------------
        beta |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
_ce1         |
price 1      |          1          .        .       .            .           .
quantity 1   |   .0599754   .0172451     3.48   0.001     .0261756    .0937753
stumpageAlog |  -.9616463   .1893601    -5.08   0.000    -1.332785   -.5905073
fin_man_co~g |   .7753336   .4594765     1.69   0.092    -.1252238    1.675891
     fin_bkt |   -.892871   .3866691    -2.31   0.021    -1.650728   -.1350136
       _cons |    3.17827          .        .       .            .           .
------------------------------------------------------------------------------

Adjustment parameters

Equation           Parms    chi2     P>chi2
-------------------------------------------
D_price 1            1   .0921779   0.7614
D_quantity 1               1   .3138968   0.5753
D_fin_stumpagep_Alog      1   10.55633   0.0012
D_fin_man_costs_sawing     1   2.658702   0.1030
D_fin_bkt                  1   .0129483   0.9094
-------------------------------------------
------------------------------------------------------------------------------
       alpha |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
D_price 1    |
        _ce1 |
         L1. |  -.0471444   .1552804    -0.30   0.761    -.3514884    .2571996
-------------+----------------------------------------------------------------
D_quantity 1 |
```

```
        _ce1 |
         L1. |   1.030623   1.839528     0.56   0.575    -2.574785    4.636031
-------------+----------------------------------------------------------------
D_stumpageAlog |
        _ce1 |
         L1. |   .1718687   .0528981     3.25   0.001     .0681903    .2755471
-------------+----------------------------------------------------------------
D_fin_man_~g |
        _ce1 |
         L1. |  -.0616375   .0378016    -1.63   0.103    -.1357273    .0124523
-------------+----------------------------------------------------------------
D_fin_bkt    |
        _ce1 |
         L1. |   .0092276   .0810925     0.11   0.909    -.1497108    .1681659
------------------------------------------------------------------------------
```

Table 15. CI- Vector and Adjustment parameters for Product 2

```
Cointegrating equations

------------------------------------------------------------------------------
        beta |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
_ce1         |
fin_price 2  |          1          .        .       .            .           .
fin_quantity2|   .1481524   .1987342     0.75   0.456    -.2413595    .5376643
stumpageBlog |  -5.584426    1.63444    -3.42   0.001    -8.787871   -2.380982
fin_man_co~g |   13.77695   3.821131     3.61   0.000     6.287668    21.26623
     fin_bkt |  -12.62461   3.342243    -3.78   0.000    -19.17529   -6.073939
       _cons |   70.56577          .        .       .            .           .
------------------------------------------------------------------------------

Adjustment parameters

Equation                Parms    chi2     P>chi2
-------------------------------------------
D_fin_Bc_Product 2_p           1   1.869031   0.1716
D_fin_Bc_Product 2_m3          1   .9207072   0.3373
D_fin_stumpagep_Blog      1   15.87171   0.0001
D_fin_man_costs_sawing     1   5.161405   0.0231
D_fin_bkt                  1   .1954027   0.6585
-------------------------------------------
------------------------------------------------------------------------------
       alpha |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
D_fin_Bc_~p |
        _ce1 |
         L1. |   .0131798   .0096406     1.37   0.172    -.0057153     .032075
-------------+----------------------------------------------------------------
D_fin_Bc~3  |
        _ce1 |
         L1. |   .1628075   .1696734     0.96   0.337    -.1697462    .4953612
-------------+----------------------------------------------------------------
D_fin_stum~g |
        _ce1 |
         L1. |   .0204013   .0051209     3.98   0.000     .0103645     .030438
-------------+----------------------------------------------------------------
D_fin_man_~g |
        _ce1 |
         L1. |  -.0073092   .0032172    -2.27   0.023    -.0136149   -.0010035
-------------+----------------------------------------------------------------
D_fin_bkt    |
```

```
        _ce1 |
         L1. |  -.0029117    .006587    -0.44   0.658     -.015822    .0099985
------------------------------------------------------------------------------
```

Table 16. CI- Vector and Adjustment parameters for Product 3

```
Cointegrating equations

------------------------------------------------------------------------------
        beta |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
_ce1         |
fin_Ab_p3    |          1          .        .       .            .           .
fin_Ab_q3    |  (omitted)
fin_~p_Alog  |   -.535058    .117555    -4.55   0.000    -.7654616   -.3046545
fin_~Afiber  |  -.3609724   .2161605    -1.67   0.095    -.7846392    .0626944
fin_man_co~g |  -1.180033   .3398398    -3.47   0.001    -1.846107    -.513959
     fin_bkt |   .7173811   .3066497     2.34   0.019     .1163587    1.318403
       _cons |  -2.789207          .        .       .            .           .
-------------+----------------------------------------------------------------
_ce2         |
fin_Ab_p3    |  (omitted)
fin_Ab_q3    |          1          .        .       .            .           .
fin_~p_Alog  |  -6.877328   1.197765    -5.74   0.000    -9.224904   -4.529751
fin_~Afiber  |   9.163112   2.202454     4.16   0.000     4.846381    13.47984
fin_man_co~g |  -2.231863   3.462619    -0.64   0.519    -9.018472    4.554746
     fin_bkt |  -3.974351   3.124446    -1.27   0.203    -10.09815    2.149451
       _cons |   43.26995          .        .       .            .           .
------------------------------------------------------------------------------

Adjustment parameters

Equation                 Parms    chi2     P>chi2
-------------------------------------------
D_fin_Ab_p3                2   9.629575   0.0081
D_ fin_Ab_q3               2   3.978025   0.1368
D_fin_stumpagep_Alog       2   4.702254   0.0953
D_fin_stumpagep_Afiber     2   3.784687   0.1507
D_fin_man_costs_sawing     2   31.74703   0.0000
D_fin_bkt                  2   4.403364   0.1106
-------------------------------------------
------------------------------------------------------------------------------
       alpha |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
D_fin_Ab_~p |
        _ce1 |
         L1. |   .1319247   .1710388     0.77   0.441    -.2033052    .4671545
             |
        _ce2 |
         L1. |   .0609136   .0221431     2.75   0.006      .017514    .1043133
-------------+----------------------------------------------------------------
D_fin_Ab~3  |
        _ce1 |
         L1. |   1.613964   1.374313     1.17   0.240    -1.079641    4.307569
             |
        _ce2 |
         L1. |  -.0736016   .1779219    -0.41   0.679    -.4223221    .2751189
-------------+----------------------------------------------------------------
D_fin_stum~g |
        _ce1 |
         L1. |   .1930013   .0910851     2.12   0.034     .0144779    .3715248
             |
```

```
        _ce2 |
         L1. |   .0126632   .0117921     1.07   0.283    -.0104489    .0357753
-------------+----------------------------------------------------------------
D_fin_stum~r |
        _ce1 |
         L1. |  -.0181838   .1125044    -0.16   0.872    -.2386884    .2023208
             |
        _ce2 |
         L1. |  -.0225725   .0145651    -1.55   0.121    -.0511196    .0059745
-------------+----------------------------------------------------------------
D_fin_man_~g |
        _ce1 |
         L1. |   .2436645   .0434854     5.60   0.000     .1584346    .3288943
             |
        _ce2 |
         L1. |   .0186158   .0056297     3.31   0.001     .0075817    .0296498
-------------+----------------------------------------------------------------
D_fin_bkt    |
        _ce1 |
         L1. |  -.2442562   .1166362    -2.09   0.036    -.4728591   -.0156534
             |
        _ce2 |
         L1. |  -.0226402      .0151    -1.50   0.134    -.0522356    .0069553
------------------------------------------------------------------------------
```

Table 17. CI- Vector and Adjustment parameters for Product 4

```
Cointegrating equations

------------------------------------------------------------------------------
        beta |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
_ce1         |
fin_Bb_p4    |          1          .        .       .            .           .
fin_Bb_q4    |   .2441327   .0717378     3.40   0.001     .1035292    .3847362
fin_~p_Blog  |  -2.002433   .3088251    -6.48   0.000     -2.60772   -1.397147
fin_~Bfiber  |   .4383245   .1532694     2.86   0.004      .137922     .738727
fin_man_co~g |  -.3748467   .5031428    -0.75   0.456    -1.360988     .611295
     fin_bkt |   1.713941   .4251489     4.03   0.000     .8806646    2.547218
       _cons |  -14.60324          .        .       .            .           .
------------------------------------------------------------------------------

Adjustment parameters

Equation                      Parms    chi2     P>chi2
-------------------------------------------
D_ fin_Bb_p4                    1   .6282691   0.4280
D_ fin_Bb_q4                    1    1.68324   0.1945
D_fin_stumpagep_Blog            1   13.21967   0.0003
D_fin_stumpagep_Bfiber          1   2.228365   0.1355
D_fin_man_costs_sawing          1   15.44842   0.0001
D_fin_bkt                       1   3.924896   0.0476
-------------------------------------------
------------------------------------------------------------------------------
       alpha |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
D_ fin_Bb_p4 |
        _ce1 |
         L1. |   .0956979    .120734     0.79   0.428    -.1409364    .3323323
```

```
-------------+----------------------------------------------------------------
D_ D_ fin_Bb_q4|
         _ce1 |
          L1. |    1.34779   1.038841     1.30   0.194    -.6883018    3.383882
-------------+----------------------------------------------------------------
D_fin_stum~g |
         _ce1 |
          L1. |   .1622117   .0446141     3.64   0.000     .0747697    .2496537

-------------+----------------------------------------------------------------
D_fin_stum~r |
         _ce1 |
          L1. |   .0822209   .0550794     1.49   0.135    -.0257327    .1901745
-------------+----------------------------------------------------------------
D_fin_man_~g |
         _ce1 |
          L1. |   .1085463   .0276168     3.93   0.000     .0544184    .1626741
-------------+----------------------------------------------------------------
D_fin_bkt    |
         _ce1 |
          L1. |  -.1216103   .0613842    -1.98   0.048    -.2419211   -.0012996
------------------------------------------------------------------------------
```

Postestimation Tests

Lagrange-multiplier test

lag	chi2	df	Prob > chi2
1	22.9814	25	0.57865
2	23.8540	25	0.52782
3	26.0044	25	0.40736
4	19.2298	25	0.78597
5	31.2592	25	0.18058
6	28.2749	25	0.29535

H0: no autocorrelation at lag order

Figure 24. LM-test for Product 1

Lagrange-multiplier test

lag	chi2	df	Prob > chi2
1	30.7814	25	0.19636
2	18.4621	25	0.82215
3	33.7607	25	0.11312
4	29.1457	25	0.25787

H0: no autocorrelation at lag order

Figure 25. LM-test for Product 2

Lagrange-multiplier test

lag	chi2	df	Prob > chi2
1	25.8905	36	0.89345
2	35.4389	36	0.49510
3	40.6485	36	0.27301
4	35.8937	36	0.47363
5	26.0178	36	0.88997
6	37.8865	36	0.38327

H0: no autocorrelation at lag order

Figure 26. LM-test for Product 3

Lagrange-multiplier test

lag	chi2	df	Prob > chi2
1	30.1302	36	0.74332
2	45.6442	36	0.13018
3	48.7414	36	0.07629
4	40.4553	36	0.28004
5	30.0970	36	0.74474
6	50.2230	36	0.05799
7	42.5231	36	0.21063

H0: no autocorrelation at lag order

Figure 27. LM-test for Product 4