Modeling Regional House Prices in the Netherlands

W.J.M. Philipsen (332809)

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Supervisors:

Erasmus University Rotterdam:

Prof. Dr. D.J.C. van Dijk

Dr. A. Pick (co-reader)

ABF Research:

Ir. C. Poulus

Abstract

This study applies panel data techniques to explore models to explain regional differences in house price developments, and to explore if the models vary per type of house or type of living environment. The Sale Price Appraisal Ratio (SPAR) method is applied to sales data from the Netherlands to create prices indices. The SPAR method uses house appraisal values to correct the price index for the mix of houses sold per time period.

Several variables for which per region time series are available are used as explanatory variables. Used are income, the total number of households, the total number of houses and the number of jobs.

The models proposed assume cointegration between prices and income. The development of prices is explained using lagged prices, the short-term shocks, and an error correction term, representing the deviation from the long-term equilibrium.

The creation of the indices from the sales data was successful, albeit challenging for the indices that were split per type of house and per type of living environment. The empirical data confirms the existence of the cointegration relationship between prices and income. Due to the presence of cross-sectional dependency, the CCEP estimation method was used. Here the cross-sectional average to the explanatory variables are added to the model to capture the unobserved variables representing the cross-sectional dependency. The standard errors for the estimated coefficients are high. The values and signs of the estimated coefficients were generally in line with expectations from economic reasoning. The estimations on the detailed indices showed that the estimated model coefficients are different depending on the type of house and the type of living environment.

Acknowledgments

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Further, I would like to thank Prof Dick van Dijk for his supervision of my thesis work and for his work in support of the masters program in Quantitative Finance.

Contents

Chapter 1

Introduction

Putting a value on a house is a complicated process. There are many factors that play a role, a lot of which are hard to quantify. For example, for houses that are at some distance, there will be vast differences in price, depending on the popularity of the area, amenities and the type of environment in general. Even for houses that are at almost the same location and are almost the same, there will be differences in maintenance and decoration. In addition, both seller and buyer may be in positions that make it harder for them to negotiate. They may be investors, but more often will be (prospective) occupants. They may be in a hurry (in dire need of a roof over their head) or may have plenty of time. All of this makes pricing an inexact process. This also complicates the making of a model for house prices, and calls for different methods than modeling other markets. Prices of houses can generally not be compared directly due to the large diversity of houses. Therefore a model will be developed for a price index, rather than for prices directly.

Most research on price models for real estate is targeted at the national level. This thesis focuses on price differences on a regional scale. Even in a small country like the Netherlands there are large regional differences in house prices. Differences can be caused be very local circumstances like noisy roads or bad neighborhoods but this work is focused on differences between regions that are larger. The main questions addressed are first, how regional differences in the development of house prices can be explained from regional differences in changes of supply and demand; second, whether the responses to shocks vary per type of house and type of living environment; and third, how the short-term shocks fit in the framework for long-term equilibrium. The goal of developing these models is to use them in combination with existing national price models for predictions and scenario analysis for regional demographics in the Netherlands.

I use the division of the Netherlands into 40 regions that is known as COROP[1]. Each region consists of a number of municipalities that border each other. The COROP division is commonly used for a lot of regional statistical research. The advantages of this division are that explanatory variable data is readily available for this division. With a division into 40 regions, there is still enough data per region to allow for the creation of the indices.

Following Holly et al. (2010) and van Dijk et al. (2011), a model is developed that describes the dynamics of price differences per region. So what are the regional differences from the national trend. The model can thus be used as a supplement to existing national models. The inputs for the model will be past prices and some variables for which regional data is available and that are expected to influence the prices, such as the number of households, houses and jobs in a region.

After looking at the per region model, two refined models are presented. For each, houses are split into groups. Separate coefficients per group are added to the estimated model to test if the response to shocks in the explanatory variables is the same between groups. The first division is by type of house. This will indicate, for example, if there is a difference in price response to an increase of supply between apartments and detached houses. The second split is by type of living environment. A living environment classifies the setting of a house, for example, in a city center with all amenities close by, or in the countryside with no neighbors. A model will then be estimated that can show if the model is the same for each group of houses.

A dataset with all sales of existing houses in the Netherlands between 1995 and 2010 is used to create price indices for houses. Having accurate price indices for small segments of the market is crucial for this research, and their creation turned out to be challenging. A key issue in transforming house sales price information into a price index is correcting for the actual houses that are sold. These can be small or large, ugly or fancy. The price index should not depend on which houses are sold in a certain period, but on the relative value of the houses. Out of the methods available, the Sale Price Appraisal Ratio (SPAR) method as developed in Bourassa

[1] It was named after the commission that came up with it in 1971, "Coördinatiecommissie Regionaal Onderzoeksprogramma".

et al. (2006) was chosen. This method uses the appraisal values available in the dataset to correct the sales prices for the properties of the houses.

First, an index is estimated that gives the value of a house per region. Further, two more indices are established, one per region and per type of house, and one per region and type of living environment. The coefficients for the model are then estimated for all three indices. As the data was found to exhibit cross-sectional dependency, the CCEP estimation as developed in Pesaran (2006) is used for the estimations.

The creation of accurate regional price indices, with splits for part of the market, was found to be a challenge. As the slice of the market became small, the existing correction techniques for the SPAR index failed, and resulted in very chaotic price indices. A simple SPAR index produced more useful price indices that were used in the estimations, but index creation needs improvement. Evidence was found to support the existence of a cointegration relationship between income and prices, and thus support for the proposed model and the underlying relationship for long-term equilibrium. The estimated coefficients for the response of prices to short-term shocks were found to be subject to large standard errors. For most the quality is not yet sufficient for use in prediction models or scenario studies. There was evidence found that the coefficients vary per type of house and per type of living environment.

The remainder of this thesis is organized as follows. Chapter 2 gives a review of literature on models for house prices and econometric techniques that are used. Chapter 3 describes the data and methods used for the creation of the price indices and the data series used as explanatory variables. In chapter 4 a model for the regional price is introduced. In addition, there is a discussion of the techniques needed to validate the model. Chapter 5 presents the results of estimating and testing the proposed model on the empirical data. And, finally, chapter 6 contains conclusions and proposals for further research.

Chapter 2

Literature

The background literature for this research can be divided into two main categories. First, there is existing work constructing price indices. It is discussed here to provide a background for the choices made in constructing the price indices in this research. Second, there is existing work on modeling house prices, and in particular modeling regional prices.

2.1 Creating price indices

A naive approach for creating a house price index is to take the average of the prices of all sales for each time period. When comparing different periods, the mix of properties sold will be different. Therefore it is of limited use to compare the average sales prices of two periods. One could compare it to creating a stock price index by taking the average of the price per share of all sales in a day, irrespective of the company.

Luckily we can do better. For each transaction there will usually be other information available. By collecting and using information about the quality of the houses that were sold each time period, it is possible to correct for the different mix between time periods. Francke et al. (2009) discuss the application of these techniques to the Dutch housing market, where indices are made by Statistics Netherlands, Calcasa[1] and OrTax[2].

[1] Calcasa used to be part of ABF Research but is now an independent company (http://www.calcasa.nl).
[2] OrTax is part of Ortec Finance (http://www.ortax.nl)

2.1.1 Simple weighted index

A first approach is to divide the sales into market segments, calculate an index per segment, and then take a weighted mean or median of the indices. This method offers a correction for differences in numbers of sales between market segments, but not for the differences of the "mix" within a segment. In the Dutch market this method is used by the NVM, the Dutch Association of Real Estate Brokers and Real Estate Experts. Also, the NVM uses the median price and not the mean price. This tends to eliminate extremes and thus has a smoothing effect.

2.1.2 Hedonic models

Another option is to collect more data about each property that is sold. Commonly used are area of the house and the lot, amenities such as garages and pools, and information about the popularity of the location. Hedonic models use a cross-sectional regression to relate sales prices to these physical and location properties. The coefficients from this regression are assumed to give the prices of the house attributes (see for example Kain and Quigley (1970); Quigley (1995)). When this regression is done for each time period, the estimated coefficients can be used to calculate a price index for a weighted average of typical houses. A problem is that detailed data for a large number of properties is not easily available. Further, it is hard to determine the correctness of the cross-sectional hedonic model, and the correctness of the composition of the index from individual house price estimates. In the Netherlands this method is used by Calcasa.

2.1.3 Repeat Sales

By collecting sales prices of the same house at different points in time, the return on a single home can be calculated. By combining these returns, an index can be calculated that is not dependent on the quality mix per time period (Quigley, 1995). Transactions for houses that sold only once can be used to improve the efficiency of the estimates, but the method mainly relies on multiple sale information. The repeat sales method is known to be sensitive to selection bias (e.g. because less wanted homes tend to change owners more often) The method is also sensitive to changes in house quality between sales. Hwang and Quigley (2004) propose a hybrid repeat sales / hedonic method to correct for the sample selection bias. The disadvantage is the added need for additional information needed for the hybrid aspect of the method.

2.1.4 Sale Price Appraisal Ratio

The sale price appraisal ratio (SPAR) method uses the ratios of the transaction prices and the appraisal values of the sold houses to correct for the quality mix between time periods (Bourassa et al., 2006). It can be seen as a special case of the hedonic model, where the only explanatory variable is the appraised value. The advantage of the method is that is relatively easy to construct. The disadvantage is that it relies on the quality of the appraisal. The index constructed by the Statistics Netherlands (CBS), the "Prijsindex Bestaande Koopwoningen," is based on this method. They use the sales data of the Dutch Land Registry Office (Kadaster) and combine it with WOZ appraisal data (De Haan et al., 2009). In this research the SPAR method will be used to create regional indices per type of house and per type of living environment.

2.2 Modeling panel time series data

The creation of the indices leads to a series of observations of the price index for each group and for each time period. Such datasets are called panel data. The dimensions will be denoted with T for the number of time periods, and N for the number of regions (commonly the word individual is used in literature). The modeling and testing methods vary a lot with the typical values for T and N, and with the correlation structure of the variables. An extensive treatment of the subject can be found in Wooldridge (2010) and Baltagi (2005).

2.2.1 The basic fixed effect and pooled panel data model

The datasets available in this research will typically contain many (40 or more) series of a smaller number (≈ 15) of observations. Estimating coefficients for each series separately is difficult due to the small number of observations. If the coefficients can be assumed to be the same across all individuals, all individual series can be used together to estimate the coefficients. This is called the “pooled panel data model”. The assumption of no differences in coefficients between individuals is in most cases not valid. A first extension is to allow for individual intercepts, while keeping the coefficients for the explanatory variables constant across individuals. This model is called the fixed effect model. Here the estimations of the coefficients for the explanatory variables still benefit from combining the individual series. The estimations of the intercepts still rely on the small number of observations in each series; adding more individuals does not improve the estimates. Both the pooling model and the fixed model are easily estimated using ordinary least squares (OLS).

2.2.2 Time series problems

The data are panels of time series. As with univariate time series, this has important consequences for the modeling and estimation. Specific for this proposal, there is a strong suspicion that the series for GDP or income and for prices are cointegrated. This means that each series is non-stationary. However, the time series share the same underlying stochastic trend. Any diversion from the common trend will dissipate over time. If the regressand and regressor(s) are non-stationary and do not share a common stochastic process, a model estimation may result in a spurious regression. The resulting R^2 may look good, but the estimation is basically garbage, describing a model that does not exist (Granger and Newbold, 1974). By differencing a variable, its random trend can be removed. The amount of differencing needed depends on the cointegration relationship. A model composed of the differenced cointegrated variables, in combination with a term that represents the temporary diversion from the long term equilibrium and stationary variables, can be estimated.

These steps are needed to detect the proper cointegration relationship. First, verify the presence of unit root in the input data: the variable itself is not stationary, but its first difference is. Second, determine a possible model for the cointegration relation and verify that the residuals of the model are stationary.

There is still a lot of development in the field of unit root testing for data panels (Breitung and Pesaran, 2008). For univariate time series the Augmented Dickey-Fuller test is the standard test method. For panel data this test needs to be augmented to allow for the presence of cross-sectional dependency. Both Holly et al. (2010) and van Dijk et al. (2011) work with similar data. Both papers calculate several test statistics. Both detect cross-sectional dependency using the CD test (Pesaran, 2004), and rely for that reason on the CIPS test (Pesaran, 2007).

2.3 Previous work on regional house prices

Malpezzi (1999) introduces an error correction model for house prices and uses regional data. They allow only the intercept to vary per region, and keep the coefficients for the other variables constant.

Brounen and Huij (2004) have an analysis for the Dutch market. They consider the price sensitivity by region and by living environment. They provide very few econometric details.

Based on housing data for the Dutch market, de Vries and Boelhouwer (2005) consider and use the change in local supply as the explanatory variable for price differences. All other coefficients are kept constant. They find that their limited dataset does indicate that a rise in supply lowers the prices.

Holly et al. (2010) develop a model that explains price differences between state in the USA using income, cost of ownership and demographic developments. Based on risk neutrality they derive a one period arbitrage condition for the market equilibrium price. Using this they make it plausible that P_t/Y_t , the ratio of price to income over time, would be stationary. Since both price and income are considered to follow unit root processes, this would imply that P_t and Y_t are cointegrated.

A similar price model is applied to Dutch market data in van Dijk et al. (2011). There are some differences in the explanatory variables that are used. The national GDP is used, as opposed to the per state per capita disposable income. There is also no demographic explanatory variable. A major model difference is the division of the regions into groups that have the same coefficient values. A method is proposed that combines the estimation of the coefficients and the formation of the groupings. The expectation was that the grouping would be driven by proximity. This seemed to be only partially the case. They also note a ripple effect; shocks in some regions are absorbed into the prices of other regions with a time delay. They apply a test flow similar to Holly et al. (2010), and end up also relying on the CD and CIPS tests for cross dependency and unit roots.

Holly et al. (2011) propose a model to further study the diffusion of price shocks between regions. Using data from the UK market, they find that shocks are faster absorbed in the time dimension then in the spacial dimension.

In this research a combination of the models in van Dijk et al. (2011) and Holly et al.

(2010). The focus will be, however, on the coefficients for short-term shock and not on the spatial effects, as they are addressed in these papers.

Chapter 3

Data

In the following sections I will describe the data that was available for the model estimations. The first section describes the creation of the price indices. For modeling regional markets, the creation of indices for small sections of the market is essential. This has a large impact on the methods that can be used for index creation.

The second section describes the source and processing for the explanatory variables. For most of the explanatory variables only annual data is available. The price indices can be created on an annual or monthly basis. The need to have as many samples as possible per time period makes an annual index the best choice.

Prices, incomes and the interest rate are corrected for inflation.

3.1 House price data

House price indices will be the dependent variable of the model. As discussed in the literature review, there are several ways to create house price indices. Indices are needed per type of house, as we want to investigate if the response to shocks in the dependent variables varies depending on the type of house. The same holds for the type of living environment. Price information for these specific groups of properties is not generally available, so needs to be created.

Table 3.1: Variables in the dataset "Bestaande Koopwoningen"

Name	Description
POOH	Unique identifier
JAARMD	transaction year and month
VKPRYS	Sales price
PHT6	6 character postal code
TYPW	type of the house
WOZW95	valuation on Jan 1st 1995, fixed on Jan 1st 1997
WOZW99	valuation on Jan 1st 1999, fixed on Jan 1st 2001
WOZW03	valuation on Jan 1st 2003, fixed on Jan 1st 2005
WOZW05	valuation on Jan 1st 2005, fixed on Jan 1st 2007
WOZW07	valuation on Jan 1st 2007, fixed on Jan 1st 2008
WOZW08	valuation on Jan 1st 2008, fixed on Jan 1st 2009
WOZW09	valuation on Jan 1st 2009, fixed on Jan 1st 2010

3.1.1 Description of the house sales dataset

The price indices will be created using data on house sales. The dataset available is the "Microdatabestand Bestaande koopwoningen" as provided by Statistics Netherlands (Centrum voor Beleidsstatistiek, 2010). All sales of existing houses to private owners in the Netherlands from January 1st 1995 until December 31st 2010 are recorded in this dataset. Table 3.1 has a description of the most important variables that are available for each sale. The sales data is collected by the Dutch Land Registry. The appraisal data are added for each record by Statistics Netherlands. These appraisal values are created by the local city governments, to provide a basis for assessing local taxes. The city governments provide Statistics Netherlands with the assessed values.

The 6 character postal code (PHT6) gives the approximate location of the property, typically to a part of a street, usually not more than 1 km long. The exact address is for privacy protection encoded in a unique identifier (POOH). Repeated sales of the same property can thus be identified, but enrichment of the data with other property specific information is not possible.

The variable TYPW describes the type of the house that was sold. Table 3.2 lists the different types.

The WOZW variables give for each sale the appraised value of the property at a few reference dates. The appraisals are made at different points in time. The standards for these appraisals are fixed by Dutch law.[1] The city where the property is located has to conduct them. For each

[1]WOZ is the abbreviation for the Dutch name of the law that mandates them: "Wet waardering onroerende

Table 3.2: Types of houses

Number	Dutch Name	English Name
1	Appartement	Apartment
2	Tussenwoning	Townhouse
3	Hoekwoning	Corner House
4	Twee onder 1 kap	Semi-Detached
5	Vrijstaand	Detached House

value there is a date for which it is valid, and a time period during which it can be adjusted. For example the WOZW95 number is issued January 1st 1997, and has the value for a property on January 1st 1995. The value can then still be revised until 1999. Even as the value is revised, the value is supposed to be the value on January 1st 1995.

The location information is detailed enough to determine for each property the region in which it is located. The division of the Netherlands into 40 COROP regions will be used (Corop40). In addition the location is used to determine the type of living environment in which the property is located. Table 3.3 lists the types that will be used.

Table 3.3: Types of living environment

Number	Dutch Name	Description
1	Centrum stedelijk (CS)	City Living close to the center
2	Stedelijk buiten centrum (BC)	City Living not in the center
3	Groen stedelijk (GS)	City living with a lot of green
4	Centrum dorps (CD)	Village center living
5	Landelijk wonen (LW)	Rural

The sales data is only available through remote access on computers located at Statistics Netherlands. Information can only be exported and used external to Statistics Netherlands, after it has been aggregated such that no individual sale information is revealed. In general this means values can only be exported if they are averages over 10 or more records.

3.1.2 Creating price indices

For the available dataset the SPAR method is the most appropriate choice to create price indices. There is not enough data on the individual objects to use hedonic methods. Creating the fine-grained indices (per region / type of house / type of environment combinations) is not feasible

zaken".

using repeat sales methods.

On the CBS statline website indices per region are available, even down to a monthly level. These indices are created using a SPAR type method and using a dataset similar to the one available for this research (van der Wal, 2008). Indices per type of house or type of living environment are not available. In some cases the index calculation has to rely on a very small number of observed sales. Such indices can not be made public, since they may reveal too much information about individual sales. Also, the quality of the index may not be high enough for general use. For this research the indices created in this way can still be used.

In the remainder of this section I will discuss the SPAR method. Next the price regional indices created with 2 variations will be compared to the regional index as published by Statistics Netherlands. Finally the indices with the splits for type of house and type of living environment will be discussed.

SPAR index construction

As the full name *Sales Price Appraisal Ratio* suggests, the index is constructed by looking at the ratio of prices to appraisal values. For each time period the sum of the prices is divided by the sum of the appraisal values for the sold properties in a certain base year.

$$I_t = \frac{\sum_{j=1}^{n_t} P_{jt} \Big/ \sum_{j=1}^{n_t} A_{jt}^k}{\sum_{j=1}^{n_k} P_{jk} \Big/ \sum_{j=1}^{n_k} A_{jk}^k} * 100 \tag{3.1}$$

Here n_t is the number of sales at time t, P_{jt} is the transaction price for the jth sale at time t, A_{jt}^k is the appraisal value at time k of the jth sale at time t. The time k is the reference time period. For this time period we need to have appraisal values for all properties. Note that the enumerator is just a constant scaling factor to ensure that $I_k = 100$. The reference time k is usually set to the first year. It can be however any year for which appraisal values are available.

The sum of appraisal values is used as correction factor for the difference in quality of the mix of properties sold. If in a given time period more expensive homes are sold, the sum of the sales prices would be very high. But in that case the sum of the appraisal values will also be high, and thus will correct the index for that. The method can be regarded as a special case of a hedonic method, where only the appraisal value is used as an indicator.

If the appraisal values in the reference year are not representative for the values at the time of the sales, the index will be less accurate. This would be the case if, for example, a home underwent some major improvements between the time of the appraisal and the time of the sale. The correction will not be large enough. As the time between the reference year and the time of the transaction increases, the problem will become worse since the appraisal values will be less representative of the relative values of the houses sold in a certain year. Another issue is houses that are built after the reference time. For those, no valid appraisal value at the reference time will be available, and the transaction has to be ignored.

A common method to alleviate these problems is to switch the reference year once a new set of appraisals becomes available. Suppose we are creating an annual index, and have appraisal values for the year 1995 and for year 1999. Our index creation starts in 1995, and 1995 is the reference year. The index is calculated this way through and including 1999. Then for 1999 and forward, the index is calculated using 1999 as the reference year. For 1999 two index values overlap. The one based on the 1995 appraisal is used to scale the new series. This way two index series can be *stitched* together. The number of samples for each reference period has to be sufficient, since the index values for those years are used to scale a complete sub series.

The quality of the index can be further improved by dividing the market into more or less homogeneous strata, calculating an index per stratum, and finally taking the weighted average of these indices.

Appraisal values

The SPAR method relies on the appraisal values to correct for the quality mix. The appraisal values in our dataset are the valuations by city governments that are used as a basis to determine property taxes. The quality of these valuations has changed over time. The general feeling is that these valuations have been too low in the past, and that there were also large differences between cities by how much it was off. A possible explanation (or conspiracy theory) of this goes as follows. The valuations are done by the local government. To limit the number of complaints from home owners, the local government could issue lower valuations and just raise the tax assessment ratio. More recently these valuations have also been used for tax assessment at the national level. This has resulted in a pattern where in the past there was more variation in the valuations and where the valuations were generally below market value. The more recent valuations are considered to be more in line with the real value. The valuation may be lagging in time, so the recent downturn in prices may not have been absorbed yet in the WOZ valuations.

Another problem is caused by the time at which the WOZ valuations are fixed. The dataset has the values at a number of reference dates (see section 3.1.1). Such a series of valuations for the same property can be used to improve a SPAR index. The latest available valuation is then used as the reference. However, the WOZ values should only be used after they do not change anymore. If these values are used to determine the index value on the date where the WOZ values can still change, there is a chance that the sales prices also propagate in the enumerator of the division of equation 3.1. It is hard to determine the exact effect, but it is clearly unwanted. There is a general belief among homeowners that cities use recent sales prices to backfill the appraisal values (and thus collect more taxes). A scan over a small number of transactions did indicate strange movements of the WOZ appraisals of properties over time. Appendix C has an analysis of the sensitivity of the WOZ values to the occurrence of a sale of the property. It is shown that this sensitivity is sizable. It looks, for example, like the recent downturn has not been absorbed into the *WOZW09* and *WOZW2010*. Only the valuations for objects that actually sold have been lowered.

Generation of the per region index

Two variants of the SPAR method have been implemented. The first creates multiple series using the newest available appraisal value, and then stitches these series together (this one will be called stitched). A similar method is used by Statistics Netherlands. We did not implement the stratification and merging. For our detailed indices there would not be enough samples per year. Also, the weights for merging were not available on the detailed scale.

A second index uses only the *WOZW07* variable[2] as a reference. In this case stitching is not needed. The *WOZW07* value was chosen for a number of reasons. Since properties that were built after that reference date do not have valid WOZ values, it is important for the reference date to be not too far in the past[3]. Houses that are demolished do not have a valid WOZW07

[2]The WOZW07 variable has the value as of January 1st 2007.

[3]Note that houses that are sold for the first time after their construction are not registered in our dataset anyway.

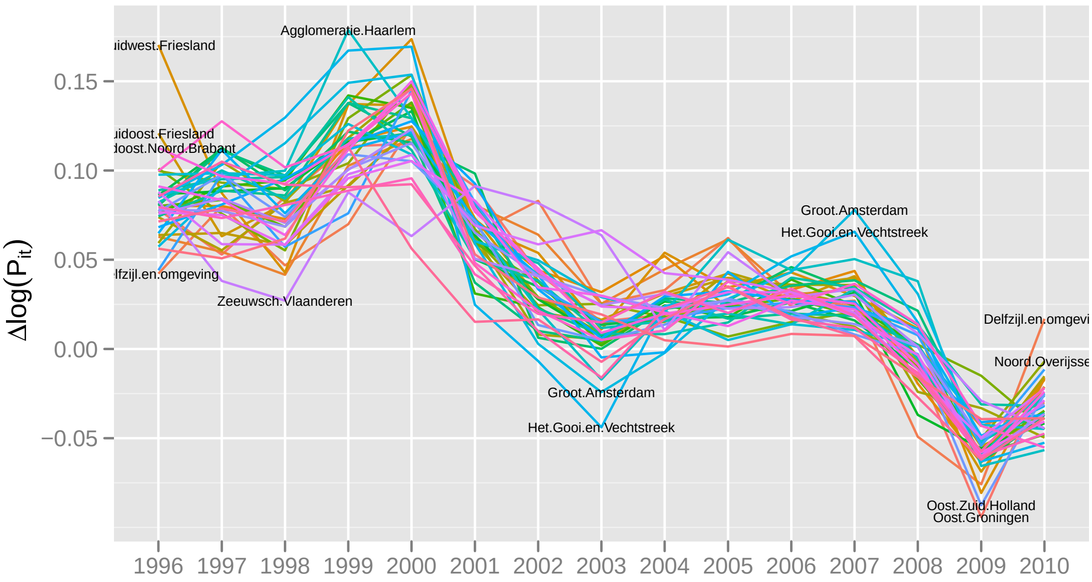

Figure 3.1: First difference of the price index per COROP region. The indices were calculated using a single WOZ value, without stitching partial series. There is one colored line per region.

value. Transactions for such homes can thus not be used in the creation of the index. This calls for an early date. The effect of the demolished homes is expected to be much smaller than the effect of new homes. Home improvements also have a negative effect on the quality of the index. In this case the value of the index will be distorted for all time periods between the reference year and the year of the improvement. These distortions will typically be small in absolute value.

For the per region index we thus have 3 price indices (between brackets the names that will be used):

- the "Price Index Owner-occupied Existing Dwellings", as published by Statistics Netherlands (CBS),
- the stitched index (*stitch*),
- the single reference year index, based on the WOZW07 valuations (*07*).

Figure 3.1 shows as an example the first differences of the log of the index as generated using the last method (*07*). Plots for the other two are in Appendix D, figures D.1 and D.2.

There are some differences between the plots, but the general picture is the same. Some differences between *CBS* and our *stitch* index are to be expected, since the *CBS* uses a stratification and merging strategy for their index. To quantify how close the indices are, the pairwise correlation of the indices per region was calculated. The first differences of log of the indices are looked at, to prevent aberrations in early years from dominating and since the model that will be introduced in the next chapter explains first differences of logs of the indices. Table 3.4 shows summary statistics of the correlation between the three indices. The complete table is in appendix D, table D.1. The differences between the *CBS* index and the other indices are the largest, due to differences in the aggregation of the means. Those differences are the largest for the rural areas. The differences between the *stitch* and the *07* indices are generally smaller. Also for this case the smallest correlation is in rural areas. There is no distinguishing difference between the *stitch* and *07* indices.

Table 3.4: Correlations between indices

	CBS - stitch	CBS - 07	stitch - 07
mean	0.964	0.963	0.975
sd	0.029	0.032	0.022
min	0.878	0.867	0.900
max	0.996	0.996	0.997

Notes: per region the correlations between pairs of first differences of the log of the indices are taken. The summary statistics of these correlations are listed here.

Separate indices per region and type

The SPAR methods as described before can be applied to create separate indices per region and type of house or living environment. They are not available from Statistics Netherlands. The generation of the *stitch* indices did not perform well. Especially for the per type of living environment index, the samples are not evenly distributed over the regions. This causes problems at the stitching points. The index creation using a single reference year did perform better. Those indices are used.[4]

Figure 3.2 shows the indices per type of living environment. The lines show the average of the index movement over the regions, per type of house and year. The overall patterns are similar. The price increase for apartments (typ = 1) were smaller than for the single family

[4]The plots for all indices are in Appendix D. Even using the single reference year method, it was not possible to generate the price index for each combination of region and type of living environment. Table D.2 lists the strata that were removed. As can be seen these are mostly city environments in rural areas.

Figure 3.2: Mean of the first difference of the log of the price index per region and type of house. For each type of house, the average of the price movements of all regions is taken.

Table 3.5: Correlation between the types of houses

	Apartment	Townhouse	Corner House	Semi-Detached	Detached House
Apartment	1.000	0.605	0.632	0.587	0.543
Townhouse	0.605	1.000	0.932	0.851	0.809
Corner House	0.632	0.932	1.000	0.869	0.822
Semi-Detached	0.587	0.851	0.869	1.000	0.832
Detached House	0.543	0.809	0.822	0.832	1.000

Notes: Each number shows the correlation between the first differences of the log of the indices of two types of houses.

homes (typ = 5). The response for apartments also seems to be delayed compared to the others.

Tables 3.5 and 3.6 show the correlation between the indices for the different types. Shown are the correlations between the first differences of the log of the price indices. First differences of the logs are used to prevent aberrations in early years from dominating.

For the type of house index, the correlation between apartment and the others is the smallest. This is to be expected; the others are all single family homes. The other correlations are also in line with expectations. For example, the detached house is most like a corner house or a semi-detached, and less like a town house.

For the type of living environments the correlations are less pronounced. Overall the differ-

Table 3.6: Correlation between the living enironments

	City Center	City Other	City Green	Village	Rural
City Center	1.000	0.723	0.740	0.789	0.687
City Other	0.723	1.000	0.815	0.860	0.753
City Green	0.740	0.815	1.000	0.871	0.748
Village	0.789	0.860	0.871	1.000	0.841
Rural	0.687	0.753	0.748	0.841	1.000

Notes: Each number shows the correlation between the first differences of the log of the indices of two types of living environment.

Table 3.7: Overview of data for explanatory variables

Variable	Description	Start[a]	Detail	Source
Y_{it}	Household income	1994	City	CBS Regionaal InkomensOnderzoek
CPI_t	Consumer Price index	1900	National	CBS
H_{it}	Number of houses	1985	City	CBS Loop van de woningvoorraad
G_{it}	Population	1995	$<$ City	CBS - Huishoudensstatistiek
r_t	Mortgage Interest	1995	National	Various
J_{it}	Number of Jobs	1996	City	LISA Vestigingenregister

[a] The starting year is given. Not every year may be available.

ences are smaller. The correlation between rural and city center is small as expected.

3.2 Data for explanatory variables

ABF research have been collecting data on many variables relating to the housing market for a long time. These datasets are used for internal research and are aggregated and prepared for use by external customers, such as local governments and housing corporations. Table 3.7 lists the original sources of the data. Below are some remarks on further processing that was done.

Income

The source of income data is the "Regional Accounts, household income" publication from Statistics Netherlands. The historic data is no longer available on the Statistics Netherlands website. For this reason data collected at ABF Research in the past has been used. For the years 1995 and 1997 no data was available. These have been estimated by linear interpolation from the numbers for 1994, 1996 and 1998. The last available data point is 2008. The data for 2009 is not expected until February 2012. For the years 2009 and 2010 income levels have been estimated to be the same as in 2008.

Population

To measure changes on the demand side, the total number of households will be used. The data is published by Statistics Netherlands in their "Huishoudensstatistiek".

Jobs

The source for the jobs data is the "LISA Vestigingenregister", as modified by ABF Research. For 1995 no data is available. No value is estimated.

Interest rate

The interest rate represents the cost to the consumer for owning a house. The average mortgage interest rate is used as an explanatory variable. Even though the actual rate a consumer pays varies depending on duration and repayment terms, it is expected to best represent the cost. The source of the data is the "Woningstatistiek" from Statistics Netherlands. The aggregation of this data available at ABF Research was used. Until 2002 the number was calculated by Statistics Netherlands from the mortgage deeds as registered at the Dutch Land Registry. From 2003 it is based on data gathered by the Dutch National Bank.

Chapter 4

Model

The goal is to create a model that explains regional differences of the development of house prices. Price indices will be the variable to be explained. First, a model will be estimated where the development of the prices per region will be explained using as explanatory variables past prices, income, population, the number of houses, number of jobs and the interest rate. Except for the interest rate, these variables are available on a regional basis. For this a fixed effect model will be estimated. This assumes that the effect of a shock in one of the explanatory variables is the same across regions. In addition there is an intercept that is different per region, and that will capture any unobserved time independent effect.

From past research there is reason to believe that prices are cointegrated with some of the explanatory variables. This is the case if prices and income have unit root, but they follow common stochastic process. The model has to be adjusted to accommodate this. If this is done properly, the residuals of the model estimation will be stationary.

Further, the model is extended to capture if the effect on prices varies per type of house or type of living environment. For this an index per type is needed.

In the following sections, first, a model is proposed for the development of regional house prices, and second, a description given of the techniques that will be used for estimating the coefficients of the model.

4.1 A proposal for a model for regional house prices

The error correction models of Holly et al. (2010) and van Dijk et al. (2011) will be my starting point. Elements of both will be used. Some regressors whose effect I want to investigate will be added. Here are the models rewritten using a common naming convention. First, Holly et al. (2010)

$$\Delta p_{it} = \alpha_i + \beta_{1i}(p_{i,t-1} - y_{i,t-1}) + \beta_{2i}\Delta p_{i,t-1} + \beta_{3i}\Delta y_{it} + \beta_{4i} g_{i,t-1} + \beta_{5i}(r_{i,t-1} - \Delta p_{i,t-1}) + \varepsilon_{it}, \quad (4.1)$$

where p_{it} and y_{it} are the logs of prices and income. They established the cointegration relationship in a separate estimation. Demographic effects are captured by $g_{i,t-1}$, the first difference of the log of the population. The last term, $r_{i,t-1} - \Delta p_{i,t-1}$, represents the net cost of borrowing. Since it also contains $\Delta p_{i,t-1}$, it captures a large part of the term for β_{2i}. They use a regional price index which results in regionally different real interest rates. The differences are limited though.

Next the model used by van Dijk et al. (2011)

$$\Delta p_{it} = \alpha_{k_i} + \beta_{1k_i}(p_{i,t-1} - \gamma_{k_i} y_{t-1}) + \beta_{2i}\Delta \bar{p}_{t-1} + \beta_{3i}\Delta y_{t-1} + \beta_{5i} r_{t-1} + \varepsilon_{it}, \quad (4.2)$$

where $\bar{p}_t$ is the average price of the houses in the Netherlands at t, and y_t is the real GDP. As opposed to the previous model they do not use regional income data, but only the national GDP. They do not fix the cointegration vector. For their estimations the model is rewritten to be linear. They estimate the α and β_1 coefficient per group of regions. The grouping of the regions is part of their estimation algorithm.

Similar to Holly et al. (2010) our model will use regional income data, and will contain the first difference of the log of the population. To measure population, the total number of households is used, since that number is expected to best capture the demographic effects on prices. The model will also include some other regressors that are expected to describe important short-term disturbances of the market. Since the payments for housing will typically be made commonly by its all inhabitants, we use the first difference of the log of the average total household income as a regressor. To capture the effect of the supply side of the market, the first difference of the log of the total number of houses per region will also be added as a regressor. As a final regressor the first difference of the log of the number of jobs will be added. The rationale is that an increase on the number of jobs in a region may indicate that more people are commuting to the region. Since this is generally regarded as a less favorable situation, it may motivate people to move to that region, and thus increase demand.

Based on the models in 4.1 and 4.2, and given the proposed regressors, I propose to use the following model:

$$\begin{aligned}\Delta p_{it} =& \alpha_i + \overbrace{\beta_1 p_{i,t-1} + \beta_2 y_{i,t-1}}^{\text{long-term adjustment}} + \beta_3 \Delta p_{i,t-1} + \beta_4 \Delta y_{it} \\ & + \underbrace{\beta_5 g_{i,t-1} + \beta_6 h_{i,t-1} + \beta_7 j_{i,t-1} + \beta_8 r_{t-1}}_{\text{response to short-term shocks}} + \varepsilon_{it}.\end{aligned} \tag{4.3}$$

where $g_{it} = \Delta log(G_{it})$, $h_{it} = \Delta log(H_{it})$ and $j_{it} = \Delta log(J_{it})$ are the first differences of the logs of population, the number of houses, and the number of jobs, respectively,[1,2] and r_t is the average mortgage interest rate. This model will be used for the price indices without differentiation for type of house and type of living environment. For the indices with those splits, the model will be augmented with different coefficients per type for β_4, β_5, β_6 and β_7. The sums of the squared residuals can be used to compare the model with and without different coefficients. An F-test can be used to verify the significance of the improvement of the model with the separate coefficients per type.

The long-term adjustment term models the return of prices to their long-term equilibrium. The ratio $\gamma = \beta_2/\beta_1$ is the price elasticity of income, and describes the cointegration elationship. The parameter $\phi = \beta_1$ is then the adjustment ratio, the speed with which prices return to their long-term equilibrium. In the model ϕ and γ are represented by β_1 and β_2 to make the model linear.

[1] The first differences of the logs of population, houses and jobs are stationary. See Appendix E for the details of the test results

[2] See Appendix F for a discussion of the results of adding the 2nd difference too.

4.2 Panel time series

4.2.1 The fixed effect model

The following is a general linear panel model,

$$y_{it} = \alpha_{ij} + X_{it}'\beta_{it} + \varepsilon_{it}, \quad i = 1, \ldots, N, \quad t = 1, \ldots, T, \quad \text{var}(\varepsilon) = \Omega. \tag{4.4}$$

where i indicates the group (in literature individual is used), t denotes time and ε is a vector of $NT \times 1$ random disturbances ε_{it}. The model in equation 4.4 has too many parameters to estimate it. Depending on the application, restrictions on the parameters are added. In our case we expect a small number for T and a larger number for N, thus the fixed effect model will be relevant. Then the following restrictions are added:

$$\alpha_{it} = \alpha_i, \quad \beta_{it} = \beta. \tag{4.5}$$

Thus the intercepts can vary per individual, but are constant over time. The slope parameters are constant across time and between individuals. The β parameters can now be interpreted as a response to the variables in X. The α_i parameters capture unobserved individual effects on y_{ij} that are constant over time. Under the usual restrictions, the parameters of this model can be estimated efficiently by OLS. The OLS estimator for α_i is consistent if $T \to \infty$. Increasing the number of individuals N does not help since each individuals adds another α_i. The OLS estimator for β is consistent if $NT \to \infty$. So for a fixed T it suffices that $N \to \infty$, since the parameters are assumed to be the same for all individuals.

When all α_i are assumed to be equal, the result is the pooling model. For given restrictions the OLS estimator has its usual properties. This implies that the restriction of all intercepts being equal $\alpha_i = \alpha$ can be tested with an F-test.[3]

4.2.2 Cross-sectional dependencies and serial correlation

The estimation and test described in the previous section are only valid if the residuals are identically and independently distributed. If there is heteroskedasticity the OLS estimator is no

[3]Besides the usual OLS assumptions, the F-test is only valid when the residuals are normally distributed.

longer efficient but still consistent. This changes if there is cross-sectional dependency between the residuals. Such dependency can be seen as unobserved variables. In this case the OLS estimates will no longer be unbiased. The presence of cross-sectional dependencies can be tested using the CD test (Pesaran, 2004). This test is valid for data panels with small values for T and that are potentially not stationary.

Cross-sectional dependencies are equivalent to the presence of unobserved common variables. The addition of these variables to the model would remove the cross-sectional dependencies. In general this is not feasible since these variables are not observed. Pesaran (2006) proposes to use the series of cross section averages of regressors and the dependent variable as proxies for these unobserved variables. By including them in the fixed effect estimation, the cross-sectional dependency can be eliminated. They call this the Common Correlated Effect estimator (CCE). The first version is the *Mean Group* estimator (CCEMG), where the coefficients for each individual are estimated separately, and then the average of the coefficients is taken. The second estimator is the pooled estimator (CCEP), where the coefficients are assumed to be the same. Pesaran (2006) reports that the CCEP estimator performed slightly better, so it will be used here. The CCEP estimator is equivalent to a fixed effect estimation, where the cross section averages are added to the model, and where the coefficients for them can vary per individual. In van Dijk et al. (2011) cross section averages are also included to eliminate cross-sectional dependencies. More details on the estimator and and the standard errors for the estimated coefficients are in Appendix G.

4.2.3 Non stationarity and cointegration

Past research indicates that the processes for prices and income are non-stationary. From a theoretical model the ratio of income to prices Y_t/P_t is expected to follow a stationary process (Holly et al., 2010). For this to hold, prices and income have to follow the same stochastic process; they have to be cointegrated. We will be looking at models for the first differences of prices and income. If prices and income are indeed cointegrated, these models need to able to accommodate this.

First, the presence of unit roots can be established by testing the time series for prices and income. Next, cointegration can be established by estimating the model:

$$p_{it} = \alpha_i + \beta y_{it} + \varepsilon_{it}. \tag{4.6}$$

If the residuals ε_{it} are stationary, and prices and income contain unit roots, they are cointegrated. The value for β describes the long-term relation between prices and income and is called the cointegration constant. From the theoretical model derived in Holly et al. (2010) it is expected to be -1.

An error correction term for the deviation from the long-term equilibrium can be added to a model for first differences:

$$\Delta p_{it} = \alpha_i + \underbrace{\phi(p_{i,t-1} - y_{i,t-1})}_{\text{error correction term}} + \beta_{1i}\Delta p_{i,t-1} + \beta_{2i}\Delta y_{it} + \varepsilon_{it} \tag{4.7}$$

To summarize, the following tests are needed:

1. verify that p_{it} and y_{it} contain a unit root
2. verify that Δp_{it} and Δy_{it} are stationary
3. verify that the residuals of the estimation of the model of equation 4.6 are stationary

Further, in order to avoid possible spurious regressions, the residuals of the model estimations need to be stationary. It is expected that my data for prices and income has similar characteristics as the datasets used in Holly et al. (2010) and van Dijk et al. (2011). The presence of cross-sectional dependency will be established using the CD test (Pesaran, 2004). In the presence of cross-sectional dependency the CIPS test (Pesaran, 2007) will be used to check for the presence of unit roots. If a variable or set of residuals does not contain cross-sectional dependency, the presence of a unit root can also be established using the IPS test (Im et al., 2003)

Chapter 5

Empirical Results

Of the three indices created in section 3.1.2, the index using only a single appraisal value as a reference (the *07* index) will be used, since this is the only index available for per type of living environment. Having indices generated using the same method should make it easier to compare the results of the estimations.[1]

First, the cointegration of prices and income will be established, followed by parameter estimations for the proposed model.

5.1 Unit Root Testing and Cointegration

The verification of the existence of cointegration between in prices and income is done in two steps. First, it is shown that both indeed contain a unit root. Second, using a model estimation it is shown that they share a common stochastic process.

Since CD-test values for both prices and income are around 110, and thus for both the hypothesis of no cross-sectional dependency is rejected, the CIPS test (Pesaran, 2007) is to be used to check for stationarity. Table 5.1 shows the results. Prices and income are commonly considered to have both an intercept and a trend. For the first differences the statistics are only reported with an intercept. The non-truncated version of the test is used. For the prices and income, the hypothesis that a unit root is present can not be rejected. For the first differences of the prices, the presence of a unit is rejected. For the first differences of the incomes it is

[1] The estimations were also done for the *CBS* and *stitch* indices, as far as available. In general the results were similar, the differences mostly insignificant. Still the differences indicate care is needed with interpreting the results.

rejected when 4 lags are allowed for. So both income and prices are not stationary, but their first differences are stationary.

Table 5.1: CIPS panel unit root results for income(y_{it}) and prices (p_{it})

	CADF(1)	CADF(2)	CADF(3)	CADF(4)
intercept only				
p_{it}	-1.96	-2.10*	-1.54	-1.52
y_{ij}	-2.77**	-1.88	-1.56	-1.32
Δp_{it}	-3.17**	-2.82**	-2.15*	-3.29**
Δy_{it}	-4.82**	-2.87**	-1.98	-2.33**
intercept and trend				
p_{it}	-2.55	-3.21**	-2.56	-3.97**
y_{ij}	-3.36**	-2.17	-1.62	-3.35**

Notes: The values show per row the $CIPS(p)$ statistics. These are the cross section averages of the cross sectionally augmented Dickey-Fuller tests statistics (Pesaran, 2007).
* significant at 5%
** significant at 1%

The next step is to confirm the cointegration relationship between prices and income, that they share a common stochastic process. For this the residuals of the estimation of the model:

$$p_{it} = \alpha_i + \beta_i y_{it} + e_{it} \tag{5.1}$$

need to be stationary. Since p_{it} and y_{it} have cross-sectional dependency, it is likely that the residuals of an ordinary fixed estimation will also. There the model is also estimated using the CCEP method. Table 5.2 shows the coefficients and test statistics for the fixed effect and CCEP estimations. The CD test shows there is indeed significant cross-sectional dependency in the residuals of the fixed effect estimation. For the CCEP estimation the hypothesis of no cross-sectional dependency can not be rejected. Since the fixed effect estimates are likely biased, we will continue working with the CCEP estimates.

Since the residuals of the CCEP estimation are free from cross-sectional dependency the IPS test can be used to verify stationarity.[2] The test statistic is -10.69, and thus the presence of a unit root is strongly rejected. The hypothesis that prices and income are not cointegrated, can

[2]The definition of the test statistic is given in equation 4.10 in Im et al. (2003). The adjustment values for mean and variance are listed in table 3 of the same paper. This test assumes T is fixed and N is sufficiently large. The plm R package (Croissant and Millo, 2008) was used to calculate the test statistics and P values.

Table 5.2: Model estimation for the cointegration relationship

	Fixed Effect		CCEP	
y_{it}	3.73	(0.09)	0.46	(0.20)
Tests				
CD	99.89	**	-1.60	
IPS	-5.18		-10.69	

Notes: The columns show the results of the fixed effect and CCEP estimations. Standard errors are shown between brackets. For the CCEP estimation this is the Newey-West type standard error as defined in equation 74 in Pesaran (2006). The listed tests are applied to the rediduals of the estimation. The CD test statistic (Pesaran, 2004) tends to $N(0,1)$ under the H_0 of no cross-sectional dependence. The IPS test statistic (Im et al., 2003, section 4) tends to $N(0,1)$ under the H_0 of a unit root.
* significant at 5%
** significant at 1%

thus be rejected.

5.2 Panel Estimates

First, panel estimates will be explored for the regional price indices for the model of equation 4.3. Later the same techniques will be applied to the more detailed indices per type of house and type of living environment.

5.2.1 Per region

The table 5.3 shows the outcome of the fixed effect and CCEP estimation of model 4.3 for the per region index. The values between brackets are the standard errors for the estimated coefficients. In the case of CCEP these are the Newey-West type standard errors as defined in equation 74 in Pesaran (2006). The non-parametric standard errors of equation 69 in the same paper were also calculated. In general these were a factor 2 higher. The calculations for these rely on the CCE Mean Group estimates, whose calculation sometimes fails due to co-linearity between regressors. For the CCEP estimation, the coefficients for the cross section averages are allow to vary per individual. The listed coefficients are the averages of the estimates for the individuals, and no standard errors are listed.

The IPS and the CIPS test both find the residuals to be stationary in both cases. The CD test for the fixed effect estimations indicates the presence of significant cross-sectional dependency in the residuals of the estimation, and that thus the estimated coefficients can be biased. The result of the CD test for the residuals of the CCEP estimation show indeed that the hypothesis of no cross-sectional dependency can not be rejected. The residuals have some skew and excess kurtosis.[3] The Jarque-Bera test rejects normality.

The fixed effect value for cointegration constant γ has with 0.24 is positive, whereas from theory -1 is expected. A positive value for γ would mean that prices decline if incomes go up, which is very unlikely from an economic perspective. For the CCEP estimation, the cointegration constant has with -0.53 the correct sign. The adjustment coefficients of -0.18 and -0.66 are larger than those reported in Holly et al. (2010) at -0.117 to -0.138 for mean group and -0.195 to -0.242 for CCEP. So according to these estimates, deviations from the long-term equilibrium would dissipate faster. Based on the CCEP estimation the halftime of a shock would be less then

[3] Throughout this report the value reported in tables will be the kurtosis and not the excess kurtosis

a year[4].

The estimated coefficients for the short-term disturbances - population, houses and jobs - show a mixed picture. The coefficient for populations is in both cases positive as expected. A rise in population should trigger a rise in demand and thus a rise in prices. For example a 1% rise in the number of households would result in approximately a 0.3% rise of the house prices.

The value of the CCEP estimation is smaller than the plain OLS estimate. For the number of houses, the fixed effect coefficient is negative as expected, but positive for the CCEP estimate. This is strange since a rise in supply should trigger a decrease of prices. The coefficient for jobs shows a similar picture. A rise in jobs is expected to increase demand.

The interest rate is an effect that is common to all regions. So for the CCEP estimation it was treated the same as the cross section averages. The coefficient for the interest rate is significant for the fixed effect estimation, but small for the CCEP estimation. It seems the CCEP estimation does a good job at already capturing common effects, and the interest rate does not improve the CCEP estimation.

It is expected that the number of households and the number of houses move together, and thus multicollinearity may be present. The high value of R^2 in combinations with large standard errors for the estimated coefficients increased suspicion of the presence of multicollinearity. The results of the Variance Inflation Factor test and Condition Number test (Belsley et al., 2004) showed that one of the cross section averages, $\Delta\bar{p}_{t-1}$, was most explained by the other variables. However, removing it from the model did not show large changes in the estimated coefficients or their standard errors.

[4]The half life of a shock in prices is about $-log(2)/log(1+\phi)$.

Table 5.3: Per region index: fixed effect and CCEP estimation.

	Fixed		CCEP	
$p_{i,t-1}$	-0.18	(0.01)	-0.66	(0.06)
$y_{i,t-1}$	-0.04	(0.05)	0.35	(0.18)
$\Delta p_{i,t-1}$	0.52	(0.03)	0.13	(0.05)
Δy_{it}	0.13	(0.05)	0.14	(0.11)
$g_{i,t-1}$	1.30	(0.26)	0.28	(0.18)
$h_{i,t-1}$	-0.45	(0.30)	0.25	(0.22)
$j_{i,t-1}$	0.06	(0.06)	-0.12	(0.03)
r_{t-1}	-0.03	(0.00)		
Derived				
γ	0.24		-0.53	
ϕ	-0.18		-0.66	
Tests				
CD	47.39	**	-1.95	
IPS	-15.06		-13.37	
CIPS(0)	-4.03	**	-4.13	**
CIPS(1)	-2.89	**	-3.26	**
skewness	-0.27		0.03	
kurtosis	3.69		3.89	
JB	16.76	**	17.73	**
R^2	0.86		0.96	

Notes: The columns show the results of the fixed effect and CCEP estimations. Standard errors are shown between brackets. For the CCEP estimation this is the Newey-West type standard error as defined in equation 74 in Pesaran (2006). The CD test statistic (Pesaran, 2004) tends to $N(0,1)$ under the H_0 of no cross-sectional dependence. The IPS test statistic (Im et al., 2003, section 4) tends to $N(0,1)$ under the H_0 of a unit root. The $CIPS(p)$ test statistics are the cross section averages of the cross sectionally augmented Dickey-Fuller tests statistics (Pesaran, 2007). The value list for the kurtosis is the moment. For the excess kurtosis subtract 3. The row labeled JB has the Jarque-Bera test statistic, which tends to $\chi^2(2)$ under the H_0 of normality. The R^2 for the CCEP estimations is the $\bar{R}^2_{CCEP}$ as defined in Holly et al. (2010).

* significant at 5%

** significant at 1%

5.2.2 Per region and type of house

For the estimations using the split indices, an individual in the context of panel data is no longer a region. In this case it is a certain type of house in a certain region. For the per type of house index that is used in this section, there are thus $40 \times 5 = 200$ individuals. The fixed effect model can be changed to allow estimates for coefficients per group of individuals. A boolean dummy variable per type is added to the panel, indicating the type of each individual. Then, to allow for separate coefficients for a variable, that variable is multiplied by each of the dummies. So, for example, for population there are now 5 variables in the model, instead of 1.

Preliminary tests showed that the CCE estimator would be most appropriate to use. The residuals for plain fixed effect estimations showed considerable cross-sectional dependency, and can thus be biased. Table 5.4 shows the results of the estimations. There are 5 sets of estimations. The *restricted* model is the same as was used in the previous section; none of the coefficients is allowed to vary between types. The estimation was done for the per type and region index, so the number of samples is larger. The columns *flex y, g, h and j* have a model where coefficients can vary for income, population, houses and jobs. The other four have a model with one of the coefficients varying.

Basic residual test results

The CD test shows that the added cross section averages capture the residual cross correlation properly. The residuals are also stationary (IPS and CIPS tests). The residuals exhibit considerable kurtosis with values around 9. The Jarque-Bera test strongly rejects normality of the residuals.

F-tests comparing splits with restricted

Table 5.4 has in the row labeled *F-split* the test statistic and significance of the test if the addition of the particular combination of split performs statistically better than the unrestricted model.

$$F = \frac{(SSR_{unres} - SSR_{res})/g}{SSR_{res}/(NT-k)} \sim F(g, NT-k). \tag{5.2}$$

Each coefficient that is allowed to fluctuate adds 5 coefficients for 1 fixed coefficient, and thus adds 4 restrictions. In the case of panel data the total number of observations is the number of individuals N times the number of time slots per series T.

Both the split for houses by itself and the combined split of income, population, houses and jobs are statistically significant at 1%. Some care must be taken with the other significance levels. These are only valid if the residuals of the regression are independent and identically normally distributed. The result of the Jarque-Bera test showed this was not the case.

Coefficients

The estimated coefficients seem robust against which combination of splits is used. If there is no split for a coefficient, its value becomes roughly the average of the coefficients in case of a split. The differences in coefficients between the individual and combined split are small. The only exception is the sensitivity for apartment prices (type 1) to changes in population, but the standard error for this coefficient is very large.

The cointegration constant γ is of the same order of magnitude as for the estimation using the per region index. The adjustment coefficient does not have a feasible value at -1.05. It would imply that diviations from the long-term equilibrium are absorbed in a single year. This seems unlikely from an economic perspective.

The sensitivity of the price of detached houses to changes in income is smaller than for other types of houses. The signs are as expected positive. For changes in population, the price sensitivity is the largest for town and corner houses. The coefficient for corner houses is the largest at 0.6. For detached houses the coefficient is negative. A positive coefficient are expected, since a rise in population would trigger a rise in demand. For the number of houses there is a large positive coefficient for detached houses (2), and a negative coefficient for apartments (-1.6). The coefficients for jobs show little variation; all are around -0.15. The p-value for the F-test was 0.8, very convincingly rejecting significance of the improvements.

Table 5.4: Per region and type of house, CCEP estimations

	Restricted	flex y	flex g	flex h	flex j	flex all
$p_{i,t-1}$	-1.04 (0.06)	-1.04 (0.06)	-1.04 (0.06)	-1.06 (0.06)	-1.04 (0.06)	-1.05 (0.06)
$y_{i,t-1}$	0.46 (0.18)	0.46 (0.18)	0.46 (0.18)	0.46 (0.18)	0.46 (0.18)	0.46 (0.18)
$\Delta p_{i,t-1}$	0.02 (0.03)	0.02 (0.03)	0.02 (0.03)	0.02 (0.03)	0.02 (0.03)	0.02 (0.03)
Δy_{it}	0.25 (0.12)		0.25 (0.12)	0.25 (0.12)	0.25 (0.12)	
Δy_{it} typ1		0.19 (0.22)				0.16 (0.21)
Δy_{it} typ2		0.30 (0.15)				0.30 (0.15)
Δy_{it} typ3		0.38 (0.13)				0.38 (0.13)
Δy_{it} typ4		0.37 (0.14)				0.39 (0.14)
Δy_{it} typ5		0.01 (0.20)				0.04 (0.19)
$g_{i,t-1}$	0.08 (0.15)	0.08 (0.15)		0.08 (0.15)	0.08 (0.15)	
$g_{i,t-1}$ typ1			-0.39 (0.47)			-0.09 (0.46)
$g_{i,t-1}$ typ2			0.17 (0.27)			0.25 (0.25)
$g_{i,t-1}$ typ3			0.53 (0.23)			0.60 (0.24)
$g_{i,t-1}$ typ4			0.11 (0.29)			-0.01 (0.29)
$g_{i,t-1}$ typ5			-0.00 (0.33)			-0.35 (0.33)
$h_{i,t-1}$	0.08 (0.22)	0.08 (0.22)	0.08 (0.22)		0.08 (0.22)	
$h_{i,t-1}$ typ1				-1.64 (0.67)		-1.59 (0.68)
$h_{i,t-1}$ typ2				-0.37 (0.41)		-0.42 (0.42)
$h_{i,t-1}$ typ3				-0.22 (0.27)		-0.33 (0.28)
$h_{i,t-1}$ typ4				0.70 (0.39)		0.75 (0.40)
$h_{i,t-1}$ typ5				1.89 (0.44)		1.97 (0.47)
$j_{i,t-1}$	-0.15 (0.03)	-0.15 (0.03)	-0.15 (0.03)	-0.15 (0.03)		
$j_{i,t-1}$ typ1					-0.21 (0.10)	-0.17 (0.10)
$j_{i,t-1}$ typ2					-0.13 (0.06)	-0.12 (0.06)
$j_{i,t-1}$ typ3					-0.14 (0.05)	-0.13 (0.05)
$j_{i,t-1}$ typ4					-0.15 (0.07)	-0.16 (0.07)
$j_{i,t-1}$ typ5					-0.10 (0.09)	-0.15 (0.09)
Derived						
γ	-0.44	-0.44	-0.44	-0.44	-0.44	-0.44
ϕ	-1.04	-1.04	-1.04	-1.06	-1.04	-1.05
Tests						
CD	-0.25	-0.27	-0.52	-0.87	-0.30	-1.08
IPS	-103.54	-87.61	-82.4	-102.04	-152.73	-136.81
F-split		1.42	1.19	15.61 **	0.33	4.60 **
skewness	-0.28	-0.28	-0.28	-0.24	-0.28	-0.23
kurtosis	8.95	8.93	8.89	8.68	8.93	8.68
JB	3576 **	3551 **	3510 **	3259 **	3559 **	3258 **
R^2	0.86	0.85	0.85	0.86	0.85	0.86

Notes: Each column shows a different choice of explanatory variables that are split by type of house. For the column *Restricted*, no splits are applied. For the column *flex all*, splits are applied for all variables. For the remaining columns the split was applied to a single variable. Standard errors are shown between brackets. The number shown is the Newey-West type standard error as defined in equation 74 in Pesaran (2006). The CD test statistic (Pesaran, 2004) tends to $N(0,1)$ under the H_0 of no cross-sectional dependence. The IPS test statistic (Im et al., 2003) tends to $N(0,1)$ under the H_0 of a unit root. The row F-split shows the F-test statistic of the colums split against the fully restricted column (see section 5.2.2 for details). The value list for the kurtosis is the moment. For the excess kurtosis subtract 3. The row labeled JB has the Jarque-Bera test statistic, which tends to $\chi^2(2)$ under the H_0 of normality. The R^2 for the CCEP estimations is the $\bar{R}^2_{CCEP}$ as defined in Holly et al. (2010).

* significant at 5%

** significant at 1%

5.2.3 Per region and type of living environment

Now dummies and split variables are added for the type of living environment, similar to the previous model. Also the index per type of living environment is used.

Basic residual test results

The results of the CD and unit root test on the residuals are similar to the results for the previous estimations. The CCEP estimator works well at removing cross-sectional dependency, and the residuals are stationary. The kurtosis of the residuals is less with values around 7, but still larger than would be the case for a normal distribution. The Jarque-Bera test rejects normality of the residuals.

F-tests comparing splits with restricted

The F-tests were performed as before. The combination of all coefficients flexible was significant at 1%. The estimation with income and population split separately were significant at 10%. Also in this case the residuals have excessive kurtosis. The results of the F-test have to be interpreted with care.

Coefficients

As was the case for the estimations using the per type of house index, the estimated coefficients are mostly robust in the choice of splits. Also, in this case the adjustment coefficient is too large at almost -1. The cointegration coefficient is closer to the theoretically expected value of -1.

The response to changes in income is smaller for rural areas (type 5) and for city green (type 3). Both types of living environment share a larger distance to amenities and shops. The parts of cities outside the city center are the most sensitive to changes in population. The city center itself and rural areas have a negative coefficient. Positive coefficients would be expected. For the number of houses, the sensitivity is the largest for parts of the city outside the center, with values of -1 and -0.4. For the other areas the coefficients are positive, where negative would be expected. Compared to the per type of house estimation, there is more spread in the coefficients for the number of jobs. They are still mostly negative around -0.12. The exception is the city green environment where the coefficient is close to 0.

Table 5.5: Per region and type of living environment, CCEP estimations

	Restricted	flex y	flex g	flex h	flex j	flex all
$p_{i,t-1}$	-0.96 (0.05)	-0.96 (0.05)	-0.96 (0.05)	-0.96 (0.05)	-0.96 (0.05)	-0.96 (0.05)
$y_{i,t-1}$	0.82 (0.20)	0.82 (0.19)	0.81 (0.19)	0.82 (0.20)	0.82 (0.20)	0.82 (0.19)
$\Delta p_{i,t-1}$	0.02 (0.04)	0.02 (0.04)	0.01 (0.04)	0.01 (0.04)	0.01 (0.04)	0.01 (0.04)
Δy_{it}	0.39 (0.13)		0.39 (0.13)	0.39 (0.13)	0.39 (0.13)	
Δy_{it} typ1		0.44 (0.29)				0.45 (0.29)
Δy_{it} typ2		0.55 (0.15)				0.54 (0.15)
Δy_{it} typ3		0.19 (0.18)				0.19 (0.18)
Δy_{it} typ4		0.58 (0.14)				0.59 (0.14)
Δy_{it} typ5		0.15 (0.20)				0.16 (0.20)
$g_{i,t-1}$	0.31 (0.17)	0.31 (0.17)		0.31 (0.17)	0.31 (0.17)	
$g_{i,t-1}$ typ1			-0.15 (0.48)			-0.22 (0.47)
$g_{i,t-1}$ typ2			0.99 (0.35)			1.17 (0.36)
$g_{i,t-1}$ typ3			0.44 (0.31)			0.48 (0.30)
$g_{i,t-1}$ typ4			0.43 (0.22)			0.35 (0.22)
$g_{i,t-1}$ typ5			-0.21 (0.39)			-0.24 (0.37)
$h_{i,t-1}$	-0.09 (0.22)	-0.10 (0.22)	-0.09 (0.22)		-0.09 (0.22)	
$h_{i,t-1}$ typ1				0.19 (0.63)		0.38 (0.64)
$h_{i,t-1}$ typ2				-0.88 (0.42)		-1.05 (0.44)
$h_{i,t-1}$ typ3				-0.23 (0.39)		-0.42 (0.43)
$h_{i,t-1}$ typ4				0.32 (0.29)		0.35 (0.29)
$h_{i,t-1}$ typ5				0.06 (0.54)		0.16 (0.57)
$j_{i,t-1}$	-0.09 (0.04)	-0.09 (0.04)	-0.09 (0.04)	-0.09 (0.04)		
$j_{i,t-1}$ typ1					-0.18 (0.10)	-0.19 (0.10)
$j_{i,t-1}$ typ2					-0.08 (0.05)	-0.07 (0.05)
$j_{i,t-1}$ typ3					0.02 (0.11)	0.03 (0.11)
$j_{i,t-1}$ typ4					-0.08 (0.04)	-0.08 (0.04)
$j_{i,t-1}$ typ5					-0.11 (0.08)	-0.12 (0.08)
Derived						
γ	-0.85	-0.85	-0.85	-0.85	-0.85	-0.85
ϕ	-0.96	-0.96	-0.96	-0.96	-0.96	-0.96
Tests						
CD	-1.34	-1.18	-1.34	-1.36	-1.49	-1.39
IPS	-40.48	-41.6	-43.61	-44.9	-43.17	-51.07
F-split		2.02	2.29	1.71	1.16	2.02 **
skewness	0.01	0.01	0.02	0.01	0.01	0.02
kurtosis	7.14	7.14	7.1	7.15	7.12	7.09
JB	1696 **	1696 **	1659 **	1700 **	1681 **	1652 **
R^2	0.86	0.86	0.86	0.86	0.86	0.86

Notes: Each colum shows a different choice of explanatory variables that are split by type of living environment. For the column *Restricted*, no splits are applied. For the column *flex all*, splits are applied for all variables. For the remaining columns the split was applied to a single variable. Standard errors are shown between brackets. The number shown is the Newey-West type standard error as defined in equation 74 in Pesaran (2006). The CD test statistic (Pesaran, 2004) tends to $N(0,1)$ under the H_0 of no cross-sectional dependence. The IPS test statistic (Im et al., 2003) tends to $N(0,1)$ under the H_0 of a unit root. The row F-split shows the F-test statistic of the colums split against the fully restricted column (see section 5.2.2 for details). The value list for the kurtosis is the moment. For the excess kurtosis subtract 3. The row labeled JB has the Jarque-Bera test statistic, which tends to $\chi^2(2)$ under the H_0 of normality. The R^2 for the CCEP estimations is the $\bar{R}^2_{CCEP}$ as defined in Holly et al. (2010).

* significant at 5%

** significant at 1%

Chapter 6

Conclusions

This thesis describes a model that explains the dynamics of regional house prices in the Netherlands. The model explains the regional deviations from the national trends. The model would thus not address the recent drop in prices since most of that occurred as a common trend across the nation. This model could be used to investigate, for example, the effects of the expected decline in population in the periphery of the Netherlands, or the effects of the planned/discussed expansions in the Northern part of the Randstad area. Further, the model is allowed to vary per type of house (apartment, detached house, etc) and per type of living environment (city center, rural, etc.). The explained variables are price indices. The price indices needed for the detailed estimations are not publicly available. These were created from a dataset with house sales data, using the SPAR method. Lags of the prices and some variables for which regional data was available and that were expected to influence regional prices differences were used as regressors. The models are estimated using panel data techniques that are suitable for panel data with cross-sectional dependencies, since this is found to be present in regressand and regressors.

The model explains first differences of the logs of the price indices. The main parts of the model are first an equation that shows how deviations from a long-term averages disappear over time. In the long-term there is a linear relation between prices and income. Such a relation is expected from theory, and it was found to be present in the data. The second part of the model describes how short shocks influence prices. The influence of demographics (the number of households and the number of jobs) and supply (the number of houses) are taken into account. For the per region index the coefficients for the long-term relation had reasonable values. The value for the coefficient describing the dissipation of deviations from the long-term equilibrium was higher then expected. The coefficient for the number of houses had a reasonable value and sign. Those for the number of houses and jobs had a sign opposite from the expected value. The most likely cause is co-linearity between the variables.

The models were also estimated where the coefficient was allowed to fluctuate between different types of houses and types of living environments. Varying coefficients were investigated for changes in income, population, houses and jobs. The splits did break up the co-linearity, resulting in more significant coefficients and more cases where the coefficients had their expected signs. The exception is the number of jobs which had a small but significant negative coefficient in all cases, whereas an increase in the number of jobs is expected to increase demand and thus prices. For the estimations of the split models, the coefficient for the speed of adjustment toward the long-term equilibrium became close to -1, which would imply deviations are absorbed immediately, which seems very unlikely.

The longer term objective of the model estimation is the generation of predictions of price developments. For population and the number of houses long-term regional predictions or estimations would be available. For income this would be harder, but the estimations show that income is an important factor that has added value for predictions. In addition, the reported standard errors for most of the estimated coefficients are so large that using these, without further improvement, for predictions and scenario analysis would not be justifiable. Better explanatory variables describing short term shocks in demand and supply might be found. Suggestions that are currently investigated include: 2nd differences for the currently used variables[1], the part of the population most likely to enter the market, and the number jobs within a reasonable travel distance instead of the number available in a region.

Looking forward, the generation of the indices can be improved by applying more accurate filtering of outliers in the sales data and possibly the application of stratification. The quality of the valuations is also a point of concern. As shown in Appendix C these seem affected by backfilling, but the extent and its effect on the calculated indices needs further exploration.

In the estimations for the split by type of house, the total number of houses was used as regressor. However, the number of houses, could also be split into separate numbers per type

[1] Preliminary results (available in Appendix F) indicate that the 2nd difference of jobs does have a significant positive effect.

of house. It is worth investigation if splitting the regressor improves the model fit. This is not certain, since the markets per type of house are expected to influence each other.

Appendix A

Explanatory variables

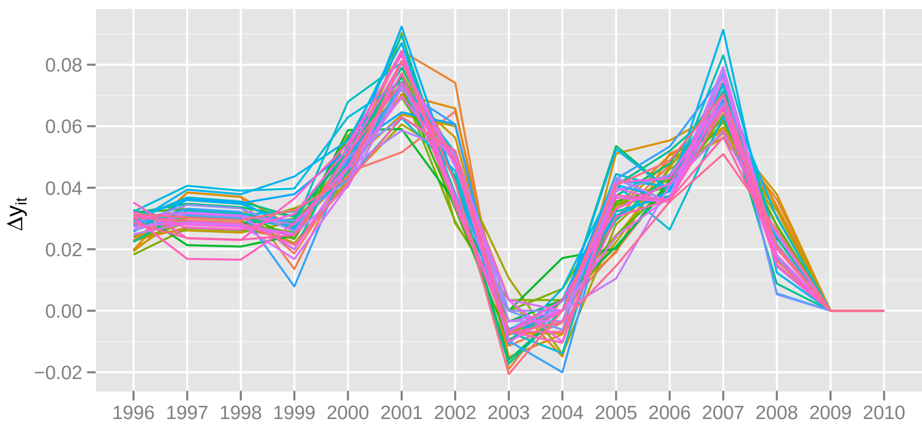

Figure A.1: Annual household income per COROP region (first diff of log)

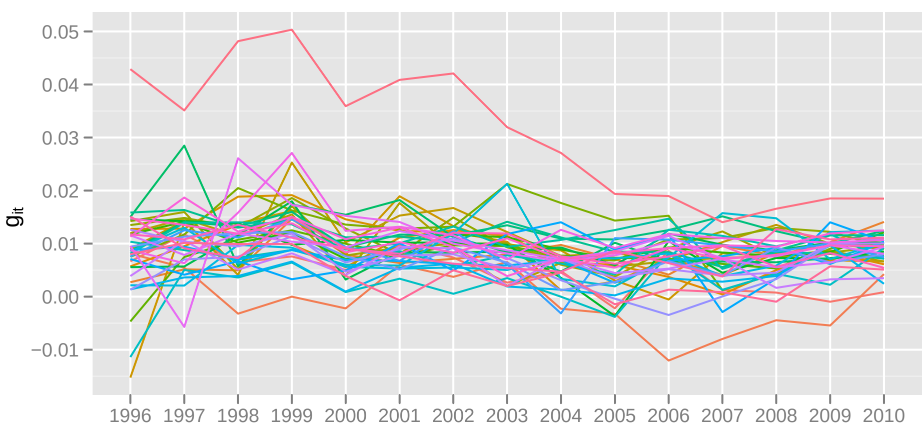

Figure A.2: Number of households per COROP region (first diff of log)

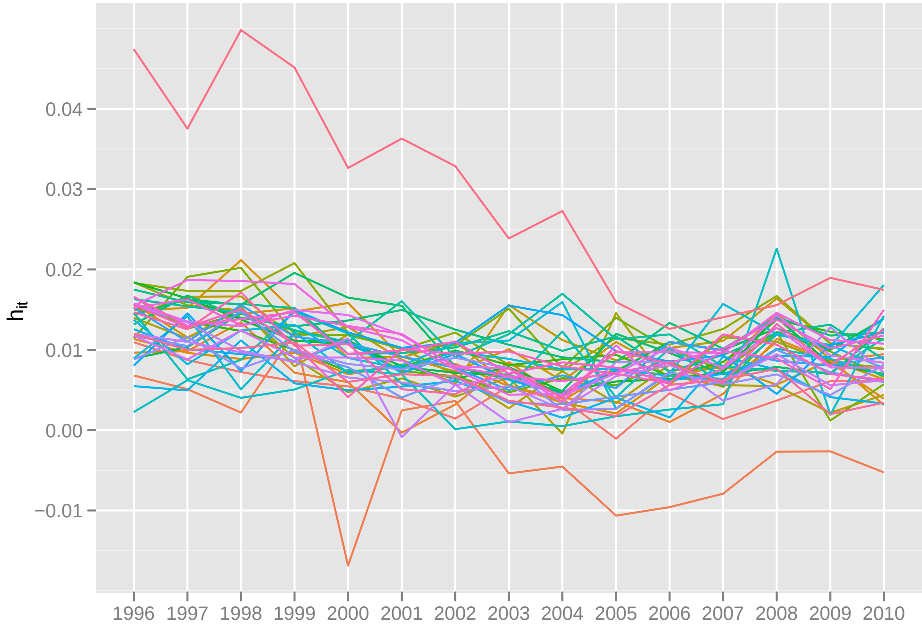

Figure A.3: Number of houses per COROP region (first diff of log)

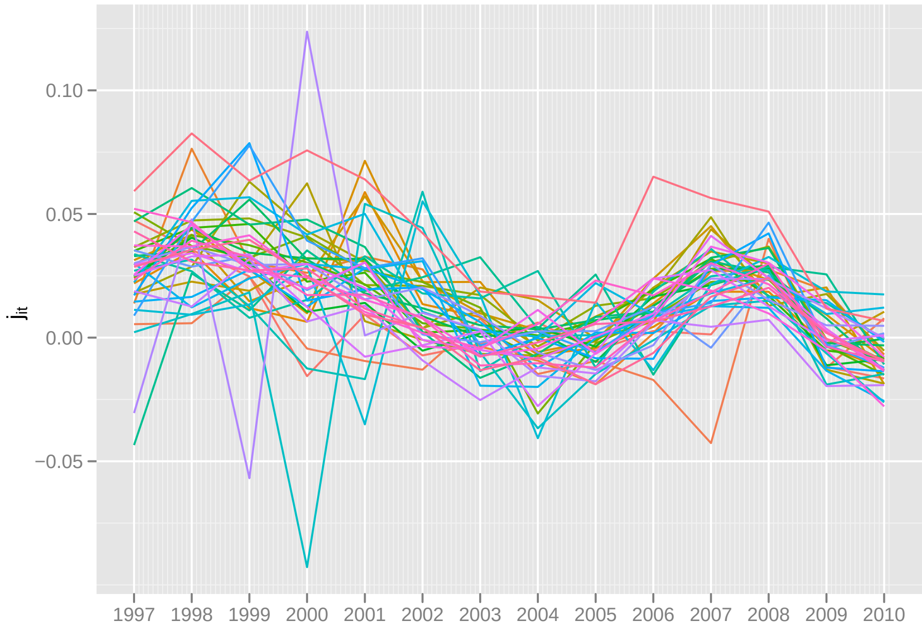

Figure A.4: Number of jobs per COROP region (first diff of log)

Appendix B

The COROP regions

Figure B.1: The division of the Netherlands into COROP regions. Source: CBS - Centraal Bureau voor de Statistiek

Appendix C

Testing for back filling of the WOZ appraisal values

A quick look at transactions for a small area revealed that the WOZ appraisal for a property may depend on the occurrence of sales over time. It seemed that after a sale, the appraisal value is adjusted towards the sale price. If the appraisals were perfect, there would not be such a dependence.

For each property that was sold at least once, there is a series of appraisal values. Each value represents the supposed value at a given measurement date. These series of WOZ values can be used to determine theoretical annual returns for each individual property. For example:

$$r_{02} = \frac{1}{4}\frac{WOZ_{03} - WOZ_{99}}{WOZ_{09}}. \tag{C.1}$$

There are 7 WOZ values, valid at January 1st 1995, 1999, 2003, 2005, 2007, 2008 and 2009. So for each property there is a series of 6 different return values, together spanning 1995 thru 2008.

first, one for each year between 1995 and 2010 that indicates whether the property sold in that year, and second, one for each year that indicates if a property was sold in the same postcode area.

From the sales records a series of dummy variables were constructed for each property: first, one for each year between 1995 and 2010 that indicates whether the property sold in that year, and second, one for each year that indicates if a property was sold in the same postal code area.

Next, an OLS regression was run with the return values as dependent variables, and the dummies as regressors. By contruction at least one of the year dummies is always 1. To prevent the system from not being identifiable, either the intercept or one of dummies needs to be left out. The Y1995 dummie, indicating a sale for the year 1995, was left out. Table C.1 shows the estimation result. The regression was run with all sold properties, so there were over 2 million observations. This causes all coefficients to be either 0 or significant.

The size of the coefficients relative to the intercept value is the largest for recent years. The influence seem large. For example, the return for the year 2007 is 0.3% lower if the property was sold in the year 2010. This is odd, since both the WOZW07 and WOZW08 values were supposedly frozen before 2010.

The results of the regression are shown graphically in figures C.1 and C.2.

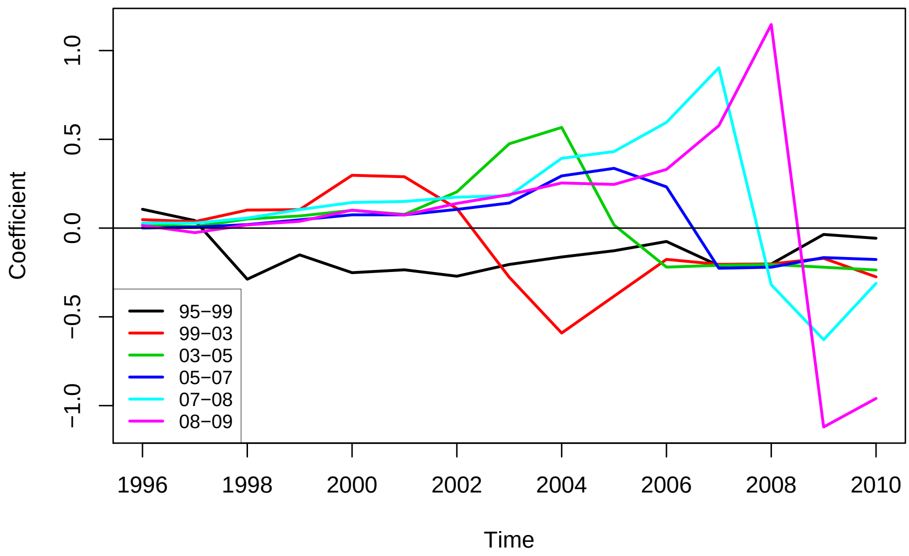

Figure C.1: Per return, dependency of year, excluding the constant. Dependency on sale of the property in a given year. The returns are in percent per year.

Table C.1: Regression of returns on sales dummies

	95-99	99-03	03-05	05-07	07-08	08-09
(Constant)	18.750	13.156	4.646	3.701	3.697	0.587
Y1996	0.106	0.048	0.018	0.001	0.028	0.015
Y1997	0.042	0.037	0.009	0.005	0.028	-0.026
Y1998	-0.288	0.101	0.051	0.020	0.056	0.018
Y1999	-0.151	0.104	0.068	0.046	0.104	0.038
Y2000	-0.251	0.297	0.100	0.075	0.144	0.101
Y2001	-0.235	0.289	0.077	0.075	0.150	0.074
Y2002	-0.271	0.110	0.204	0.105	0.174	0.139
Y2003	-0.205	-0.277	0.475	0.141	0.183	0.188
Y2004	-0.163	-0.591	0.567	0.294	0.393	0.254
Y2005	-0.128	-0.383	0.017	0.336	0.431	0.246
Y2006	-0.075	-0.176	-0.220	0.232	0.595	0.330
Y2007	-0.211	-0.204	-0.210	-0.226	0.903	0.577
Y2008	-0.202	-0.202	-0.205	-0.220	-0.319	1.147
Y2009	-0.036	-0.170	-0.220	-0.166	-0.629	-1.120
Y2010	-0.057	-0.275	-0.236	-0.177	-0.311	-0.960
Pc Y1995	-0.515	-0.010	0.044	-0.022	-0.119	-0.021
Pc Y1996	-0.752	-0.022	0.005	-0.012	-0.159	-0.066
Pc Y1997	-0.569	0.006	-0.029	-0.014	-0.091	-0.033
Pc Y1998	-0.989	0.053	-0.078	-0.064	-0.092	-0.042
Pc Y1999	-0.644	-0.049	-0.020	-0.064	-0.155	-0.045
Pc Y2000	-0.470	-0.004	0.020	-0.001	-0.064	-0.011
Pc Y2001	-0.357	-0.041	-0.008	-0.058	-0.054	-0.045
Pc Y2002	-0.427	-0.149	-0.020	-0.039	-0.037	-0.022
Pc Y2003	-0.432	-0.250	-0.034	-0.004	-0.035	-0.012
Pc Y2004	-0.214	-0.161	-0.198	0.025	0.032	0.034
Pc Y2005	-0.337	-0.154	-0.279	-0.021	0.031	0.027
Pc Y2006	-0.155	-0.188	-0.191	-0.103	0.033	0.046
Pc Y2007	-0.208	-0.067	-0.160	-0.144	-0.169	0.044
Pc Y2008	-0.081	-0.062	-0.162	-0.027	-0.153	-0.059
Pc Y2009	-0.024	-0.084	-0.162	-0.008	-0.049	-0.212
Pc Y2010	-0.077	-0.055	-0.099	0.025	0.091	-0.094

Notes: The returns are in percent per year and are calculated from the WOZ values that are available for certain reference dates. The dummy variables indicate if a property was sold in given year, or if a property in the same area (same postal code) was sold in a given year.

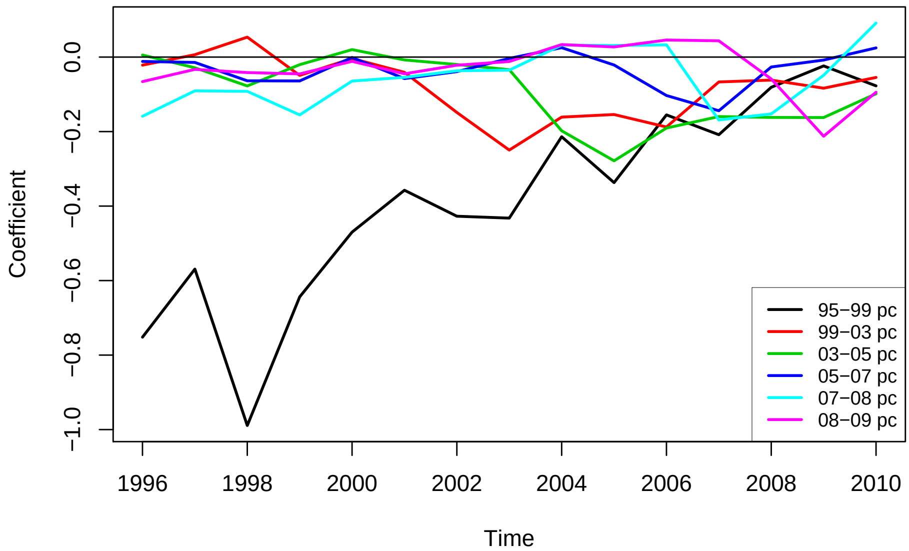

Figure C.2: Per return, dependency of year, excluding the constant. Dependency on sale in the same postal code area in a given year. The returns are in percent per year.

Table C.2: Per region CCEP estimation for different index types

	CBS	Stitch	07
$p_{i,t-1}$	-0.75 **	-0.70 (0.05)	-0.66 ** (0.06)
$y_{i,t-1}$	0.83 **	0.55 (0.24)	0.35 (0.18)
$\Delta p_{i,t-1}$	-0.04	-0.06 (0.05)	0.13 ** (0.05)
Δy_{it}	0.43 **	0.46 (0.14)	0.14 (0.11)
$g_{i,t-1}$	0.31	0.24 (0.20)	0.28 (0.18)
$h_{i,t-1}$	-0.21	0.38 (0.28)	0.25 (0.22)
$j_{i,t-1}$	-0.10 **	-0.13 (0.04)	-0.12 ** (0.03)
r_{t-1}	-0.00	-0.00	-0.00
$\bar{p}_{t-1}$	0.74	0.70	0.65
$\bar{y}_{t-1}$	-0.78	-0.52	-0.31
$\Delta\bar{p}_t$	1.00	1.01	1.00
$\Delta\bar{p}_{t-1}$	0.06	0.08	-0.10
$\Delta\bar{y}_t$	-0.42	-0.46	-0.14
intp	-0.10	-0.10	-0.10
Derived			
γ	-1.11	-0.78	-0.53
ϕ	-0.75	-0.7	-0.66
Tests			
R^2	0.96	0.96	0.96

* significant at 5%
** significant at 1%

C.1 Analyzing residuals

The plots for the residuals of the regressions as performed in chapter 5 seemed to indicate that the residuals were a lot smaller around the year 2007. This section shows the results of comparing the residuals of the estimations for the three region-based indices: *CBS*, *Stitch* and *07*. The plain CCEP estimation resultsare listed in table C.2.

The estimates for the CBS index are more in line with the values expected from theory. The coefficient for population is positive, and the coefficient for houses is negative. The γ is close to 1. The plots on the following pages show the residuals. The basic conclusion: The differences do not seem to be substantial. The same dip in the residuals for 2006 appears in the residuals for all three estimations.

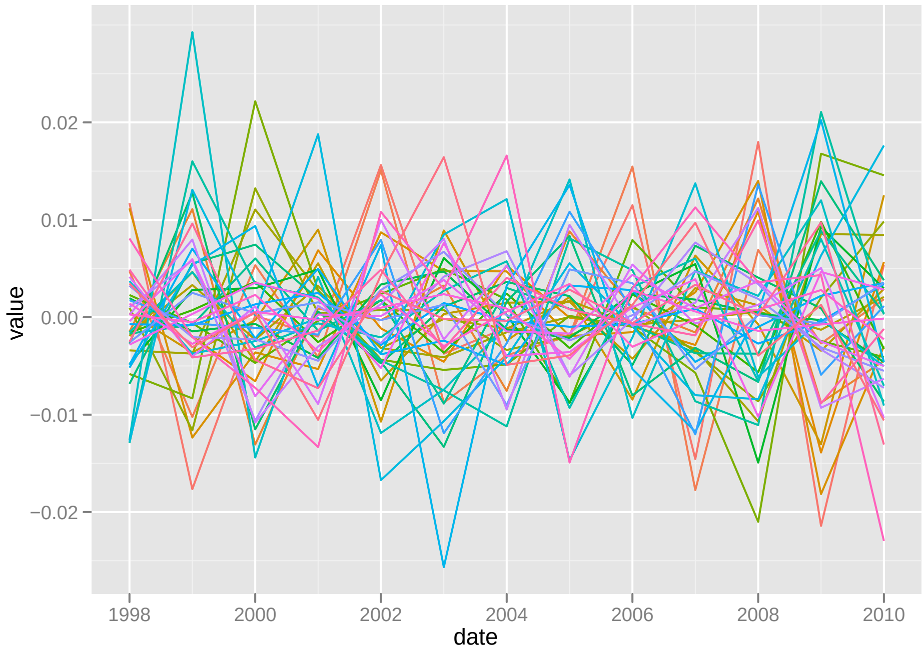

Figure C.3: Residuals CBS index

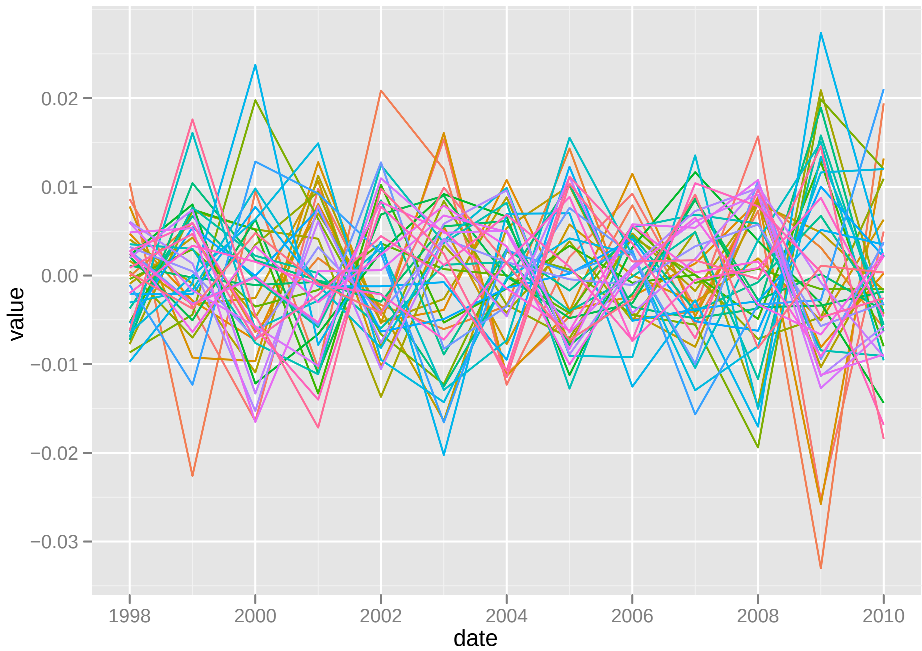

Figure C.4: Residuals Stitch index

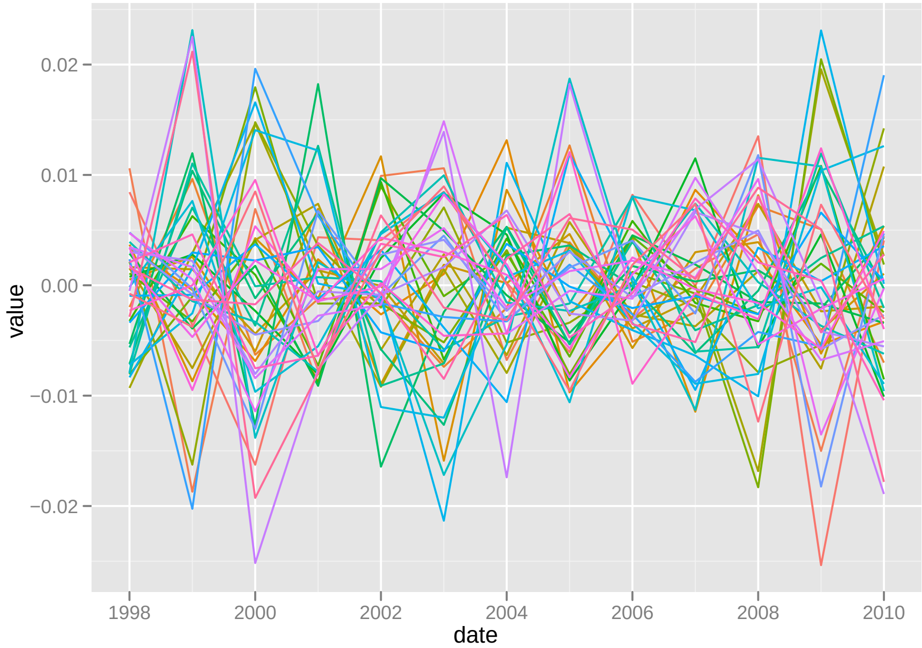

Figure C.5: Residuals 07 index

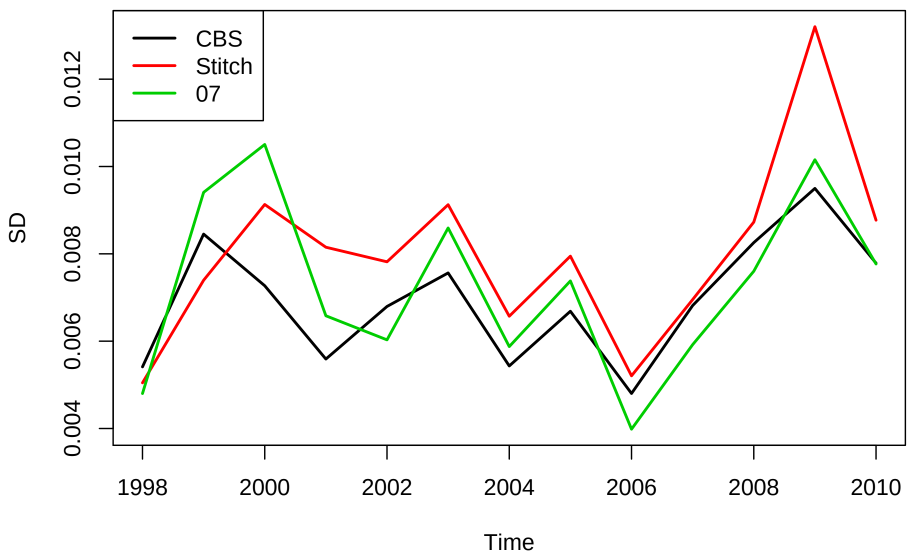

Figure C.6: Standard deviation of the residuals over time

Appendix D

Price index creation

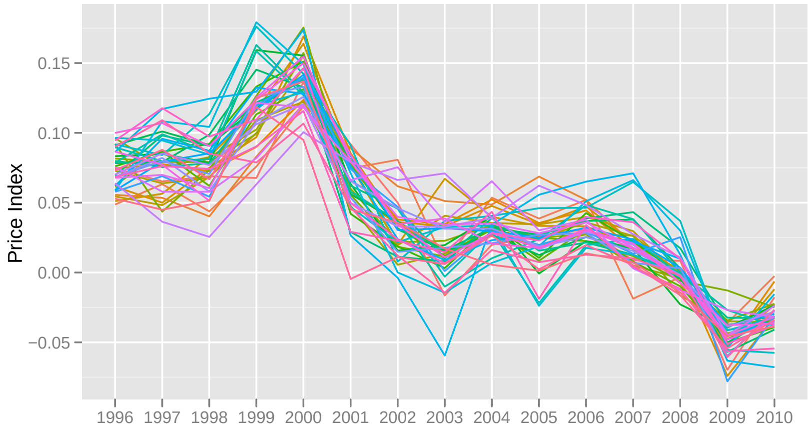

Figure D.1: Index per COROP region, CBS PBK

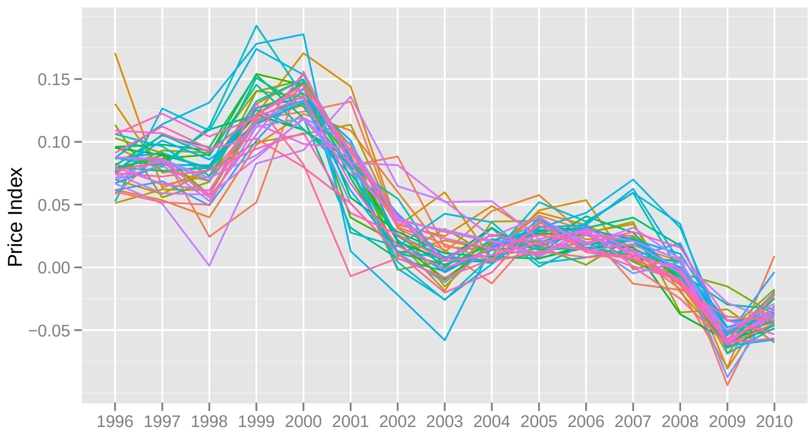

Figure D.2: Index per COROP region, Stiching multiple sub series

Table D.1: Per region the correlation between indices

	CBS - stitch	CBS - 07	stitch - 07
Oost.Groningen	0.930	0.938	0.966
Delfzijl.en.omgeving	0.921	0.867	0.929
Overig.Groningen	0.949	0.964	0.984
Noord.Friesland	0.985	0.971	0.975
Zuidwest.Friesland	0.882	0.871	0.900
Zuidoost.Friesland	0.897	0.889	0.981
Noord.Drenthe	0.941	0.952	0.977
Zuidoost.Drenthe	0.932	0.970	0.925
Zuidwest.Drenthe	0.948	0.957	0.985
Noord.Overijssel	0.955	0.981	0.973
Zuidwest.Overijssel	0.958	0.961	0.976
Twente	0.991	0.983	0.985
Veluwe	0.987	0.992	0.993
Achterhoek	0.953	0.952	0.985
Arnhem.Nijmegen	0.996	0.996	0.992
Zuidwest.Gelderland	0.984	0.964	0.967
Utrecht	0.980	0.986	0.996
Kop.van.Noord.Holland	0.981	0.977	0.989
Alkmaar.en.omgeving	0.975	0.984	0.974
IJmond	0.972	0.949	0.980
Agglomeratie.Haarlem	0.966	0.964	0.990
Zaanstreek	0.978	0.970	0.947
Groot.Amsterdam	0.992	0.984	0.982
Het.Gooi.en.Vechtstreek	0.974	0.980	0.996
Agglomeratie.Leiden.en.Bollenstreek	0.981	0.971	0.980
Agglomeratie..s.Gravenhage	0.979	0.982	0.991
Delft.en.Westland	0.981	0.939	0.960
Oost.Zuid.Holland	0.981	0.968	0.978
Groot.Rijnmond	0.977	0.988	0.977
Zuidoost.Zuid.Holland	0.974	0.990	0.980
Zeeuwsch.Vlaanderen	0.878	0.897	0.916
Overig.Zeeland	0.979	0.940	0.966
West.Noord.Brabant	0.980	0.979	0.984
Midden.Noord.Brabant	0.989	0.991	0.997
Noordoost.Noord.Brabant	0.993	0.989	0.992
Zuidoost.Noord.Brabant	0.983	0.987	0.992
Noord.Limburg	0.965	0.965	0.989
Midden.Limburg	0.964	0.982	0.986
Zuid.Limburg	0.974	0.949	0.979
Flevoland	0.971	0.995	0.978

Notes: Per region the correlation between the series of first difference of the log of the price indices are calculated. The gray lines are those with the 10 smallest correlations.

Table D.2: Missing type of environment indices

Corop region	Type of environment
Oost Groningen	City Center
Oost Groningen	City Other
Oost Groningen	City Green
Delfzijl en omgeving	City Center
Delfzijl en omgeving	City Other
Delfzijl en omgeving	City Green
Noord Friesland	City Center
Zuidwest Friesland	City Center
Zuidoost Drenthe	City Other
Zuidwest Overijssel	City Green
IJmond	City Green
Zaanstreek	City Green
Zaanstreek	Rural
Het Gooi en Vechtstreek	Rural
Delft en Westland	City Green
Delft en Westland	Rural
Zeeuwsch Vlaanderen	City Center
Flevoland	City Center

Notes: The combinations of region and type of living environment for which no valid index could be produced.

Appendix E

Unit root tests for populations, houses and jobs.

Table E.1 shows the CIPS unit root test results for the explanatory variables (population, houses and jobs) and their first differences. The first difference of population is stationary. Both houses and jobs are stationary without differencing.

Table E.1: CIPS panel unit root results for income(y_{it}) and prices (p_{it})

	CADF(1)	CADF(2)	CADF(3)	CADF(4)
intercept only				
g_{ij}	-1.5	-1.86	-1.46	-1.65
h_{ij}	-2.03	-2.27**	-2.39**	-2.17*
j_{ij}	-2.22**	-2.21**	-2.38**	
Δg_{ij}	-2.7**	-2.25**	-2.15*	
Δh_{ij}	-2.97**	-2.41**	-2.3**	
Δj_{ij}	-3.65**	-2.76**		

Notes: The values show per row the $CIPS(p)$ statistics. These are the cross section averages of the cross sectionally augmented Dickey-Fuller tests statistics (Pesaran, 2007). For entries without a value, one of the auxiliary regressions failed.
* significant at 5%
** significant at 1%

Appendix F

Regression using 2nd differences

In this chapter are the results of experiments adding the 2nd difference of population, houses and jobs as short-term shocks to the model of equation 4.3.

The 2nd difference of jobs seems to be influential, especially in combination with the split for type of house. However, the resulting estimate for the cointegration constant seems unlikely from an economic perspective. In addition, cross-sectional dependency seems to be added, which may cause the results to be biased.

F.1 Adding the 2nd differences to the regional estimation

Table F.1 shows the results of adding the 2nd differences to the model, and estimating it for the panel with the per region data. The column *Plain* repeats the results of sections 5.2.1. The middle three columns show a model with each of the variables added individually. The last column shows a model with all three added. *Due to software limitations, currently the length of the panel is 13 for the Plain, 12 for the others.*

The estimated coefficients for population and houses are not significant.

The coefficient for jobs is significant. The results of the F-test in the last column suggests that the combined addition of 2nd differences of population, houses and jobs also significantly increases the fit. In both cases, the cointegration constant decreases to about 0.25, which is, from an economic perspective, not very likely. The sole addition of jobs seems to cause significant cross-sectional dependency in the residuals. This raises the concern for bias in the estimated

Table F.1: Model estimations with 2nd differences, per region panel

	Plain	added 2nd g	added 2nd h	added 2nd j	added 2nd all
$p_{i,t-1}$	-0.66 (0.06)	-0.65 (0.06)	-0.65 (0.06)	-0.75 (0.06)	-0.75 (0.06)
$y_{i,t-1}$	0.35 (0.18)	0.36 (0.19)	0.36 (0.18)	0.19 (0.21)	0.20 (0.21)
$\Delta p_{i,t-1}$	0.13 (0.05)	0.12 (0.05)	0.12 (0.05)	0.04 (0.05)	0.03 (0.05)
Δy_{it}	0.14 (0.11)	0.15 (0.11)	0.14 (0.11)	0.01 (0.12)	0.03 (0.12)
$g_{i,t-1}$	0.28 (0.18)	0.47 (0.28)	0.26 (0.19)	0.61 (0.19)	0.71 (0.34)
$\Delta g_{i,t-1}$		-0.13 (0.18)			-0.10 (0.21)
$h_{i,t-1}$	0.25 (0.22)	0.23 (0.22)	0.51 (0.34)	-0.03 (0.22)	0.22 (0.43)
$\Delta h_{i,t-1}$			-0.19 (0.22)		-0.18 (0.23)
$j_{i,t-1}$	-0.12 (0.03)	-0.12 (0.03)	-0.12 (0.03)	-0.24 (0.08)	-0.24 (0.08)
$\Delta j_{i,t-1}$				0.10 (0.04)	0.11 (0.04)
r_{t-1}	-0.00	-0.00	-0.00	-0.00	-0.00
$\bar{p}_{t-1}$	0.65	0.65	0.65	0.72	0.72
$\bar{y}_{t-1}$	-0.31	-0.32	-0.33	-0.12	-0.14
$\Delta\bar{p}_t$	1.00	0.99	1.00	0.92	0.93
$\Delta\bar{p}_{t-1}$	-0.10	-0.09	-0.10	0.03	0.03
$\Delta\bar{y}_t$	-0.14	-0.14	-0.14	0.00	-0.01
intp	-0.10	-0.10	-0.10	-0.02	-0.04
Derived					
γ	-0.53	-0.55	-0.54	-0.25	-0.26
ϕ	-0.66	-0.65	-0.65	-0.75	-0.75
Tests					
CD	-1.95	-1.76	-1.58	-1.96 **	-1.70
IPS	-13.37	-15.35	-14.42	-26.08	-20.64
CIPS(0)	-4.13 **	-4.23 **	-4.77 **	-5.75 **	-4.76 **
CIPS(1)	-3.26 **	-3.31 **	-3.63 **	-2.55 **	-2.53 **
F-split		0.75	1.22	151.88 **	51.22 **
skewness	0.03	0.02	0.01	0.01	-0.01
kurtosis	3.89	3.85	3.87	3.98	3.92
JB	17.73 **	16.37 **	16.95 **	19.80 **	17.41 **
R^2	0.96	0.96	0.96	0.96	0.96

Notes: The columns show the results of the fixed effect and CCEP estimations. Standard errors are shown between brackets. For the CCEP estimation this is the Newey-West type standard error as defined in equation 74 in Pesaran (2006). The CD test statistic (Pesaran, 2004) tends to $N(0,1)$ under the H_0 of no cross-sectional dependence. The IPS test statistic (Im et al., 2003, section 4) tends to $N(0,1)$ under the H_0 of a unit root. The row F-split shows the F-test statistic of the columns split against the fully restricted column (see section 5.2.2 for details). The $CIPS(p)$ test statistics are the cross section averages of the cross sectionally augmented Dickey-Fuller test statistics (Pesaran, 2007). The value list for the kurtosis is the moment. For the excess kurtosis subtract 3. The row labeled JB has the Jarque-Bera test statistic, which tends to $\chi^2(2)$ under the H_0 of normality. The R^2 for the CCEP estimations is the $\bar{R}^2_{CCEP}$ as defined in Holly et al. (2010).

* significant at 5%

** significant at 1%

coefficients.

Very similar results are observed if these models are estimated for the data panels that have the split prices by type of house and type of living environment. These results are tabulated in the tables F.2 and F.3.

F.2 Exploring the influence of the 2nd diff of jobs per type of house and type of living environment

As for the model in 4.3, the influence of the 2nd difference of jobs per type of house and per type of living environment can be estimated by adding dummy variables to the estimation for the data panels with the detailed data. This was done only for the 2nd difference of jobs, since this was the only 2nd difference that had significant parameters. The results for these estimations are shown in tables F.4 and F.5.

The results of the F-test suggest that the coefficient for the 2nd difference of jobs is indeed significantly different for the per type of house data panel. For apartments it is about twice as large. For the per type of living environment data panel, the F-test suggests there is not a significant difference in coefficients.

Table F.2: Model estimations with 2nd differences, per region and type of house panel

	Plain	added 2nd g	added 2nd h	added 2nd j	added 2nd all
$p_{i,t-1}$	-1.04 (0.06)	-1.04 (0.06)	-1.04 (0.06)	-1.32 (0.06)	-1.32 (0.06)
$y_{i,t-1}$	0.46 (0.18)	0.46 (0.18)	0.49 (0.19)	0.03 (0.19)	0.09 (0.19)
$\Delta p_{i,t-1}$	0.02 (0.03)	0.02 (0.03)	0.02 (0.03)	0.10 (0.03)	0.10 (0.04)
Δy_{it}	0.25 (0.12)	0.26 (0.12)	0.28 (0.12)	-0.10 (0.11)	-0.05 (0.12)
$g_{i,t-1}$	0.08 (0.15)	0.40 (0.33)	0.03 (0.15)	0.45 (0.17)	0.02 (0.34)
$\Delta g_{i,t-1}$		-0.22 (0.20)			0.23 (0.20)
$h_{i,t-1}$	0.08 (0.22)	0.04 (0.22)	0.84 (0.41)	-0.07 (0.23)	0.99 (0.40)
$\Delta h_{i,t-1}$			-0.56 (0.26)		-0.69 (0.25)
$j_{i,t-1}$	-0.15 (0.03)	-0.14 (0.03)	-0.15 (0.03)	-0.37 (0.06)	-0.40 (0.06)
$\Delta j_{i,t-1}$				0.16 (0.03)	0.18 (0.03)
r_{t-1}	0.00	0.00	0.00	-0.00	0.00
$\bar{p}_{t-1}$	1.03	1.02	1.04	1.27	1.30
$\bar{y}_{t-1}$	-0.40	-0.40	-0.44	0.07	-0.02
$\Delta\bar{p}_t$	1.03	1.02	1.03	0.92	0.96
$\Delta\bar{p}_{t-1}$	-0.02	-0.02	-0.04	-0.01	-0.04
$\Delta\bar{y}_t$	-0.25	-0.24	-0.27	0.10	0.03
intp	-0.17	-0.20	-0.16	-0.26	-0.22
Derived					
γ	-0.44	-0.45	-0.47	-0.02	-0.07
ϕ	-1.04	-1.04	-1.04	-1.32	-1.32
Tests					
CD	-0.25	-0.47	-0.96	3.64 **	2.00 **
IPS	-103.54	-100.26	-158.26	NaN	NaN
F-split		1.94	8.54 **	1238.95 **	419.13 **
skewness	-0.28	-0.29	-0.32	-0.34	-0.36
kurtosis	8.95	8.97	8.92	7.92	7.93
JB	3576 **	3607 **	3561 **	2269 **	2278 **
R^2	0.86	0.86	0.86	0.89	0.89

Notes: The columns show the results of the fixed effect and CCEP estimations. Standard errors are shown between brackets. For the CCEP estimation this is the Newey-West type standard error as defined in equation 74 in Pesaran (2006). The CD test statistic (Pesaran, 2004) tends to $N(0,1)$ under the H_0 of no cross-sectional dependence. The IPS test statistic (Im et al., 2003, section 4) tends to $N(0,1)$ under the H_0 of a unit root. The row F-split shows the F-test statistic of the columns split against the fully restricted column (see section 5.2.2 for details). The $CIPS(p)$ test statistics are the cross section averages of the cross sectionally augmented Dickey-Fuller test statistics (Pesaran, 2007). The value list for the kurtosis is the moment. For the excess kurtosis subtract 3. The row labeled JB has the Jarque-Bera test statistic, which tends to $\chi^2(2)$ under the H_0 of normality. The R^2 for the CCEP estimations is the $\bar{R}^2_{CCEP}$ as defined in Holly et al. (2010).

* significant at 5%

** significant at 1%

Table F.3: Model estimations with 2nd differences, per region and type of living environment panel

	Plain	added 2nd g	added 2nd h	added 2nd j	added 2nd all
$p_{i,t-1}$	-0.96 (0.05)	-0.96 (0.05)	-0.96 (0.05)	-1.10 (0.06)	-1.10 (0.06)
$y_{i,t-1}$	0.82 (0.20)	0.83 (0.20)	0.83 (0.20)	0.47 (0.21)	0.47 (0.22)
$\Delta p_{i,t-1}$	0.02 (0.04)	0.01 (0.04)	0.01 (0.04)	0.03 (0.04)	0.02 (0.04)
Δy_{it}	0.39 (0.13)	0.40 (0.13)	0.40 (0.13)	0.15 (0.13)	0.17 (0.13)
$g_{i,t-1}$	0.31 (0.17)	0.67 (0.29)	0.26 (0.17)	0.73 (0.18)	1.03 (0.31)
$\Delta g_{i,t-1}$		-0.26 (0.16)			-0.25 (0.17)
$h_{i,t-1}$	-0.09 (0.22)	-0.13 (0.22)	0.34 (0.35)	-0.07 (0.24)	0.23 (0.43)
$\Delta h_{i,t-1}$			-0.33 (0.23)		-0.22 (0.23)
$j_{i,t-1}$	-0.09 (0.04)	-0.08 (0.04)	-0.08 (0.04)	-0.32 (0.08)	-0.31 (0.08)
$\Delta j_{i,t-1}$				0.17 (0.04)	0.18 (0.04)
r_{t-1}	-0.00	-0.00	-0.00	-0.00	-0.00
$\bar{p}_{t-1}$	0.96	0.95	0.96	1.06	1.06
$\bar{y}_{t-1}$	-0.79	-0.78	-0.81	-0.39	-0.40
$\Delta\bar{p}_t$	0.99	0.98	0.99	0.90	0.90
$\Delta\bar{p}_{t-1}$	0.01	0.01	0.01	0.06	0.05
$\Delta\bar{y}_t$	-0.39	-0.38	-0.40	-0.14	-0.16
intp	-0.11	-0.13	-0.08	-0.20	-0.20
Derived					
γ	-0.85	-0.86	-0.86	-0.42	-0.43
ϕ	-0.96	-0.96	-0.96	-1.1	-1.1
Tests					
CD	-1.34	-0.60	-0.50	-0.81	-0.37
IPS	-40.48	-46.47	-42.79	-66.82	-86.37
F-split		2.97	3.48	861.76 **	290.02 **
skewness	0.01	0	0	0.1	0.08
kurtosis	7.14	7.1	7.13	7.21	7.08
JB	1696 **	1665 **	1683 **	1618 **	1525 **
R^2	0.86	0.86	0.86	0.88	0.88

Notes: The columns show the results of the fixed effect and CCEP estimations. Standard errors are shown between brackets. For the CCEP estimation this is the Newey-West type standard error as defined in equation 74 in Pesaran (2006). The CD test statistic (Pesaran, 2004) tends to $N(0,1)$ under the H_0 of no cross-sectional dependence. The IPS test statistic (Im et al., 2003, section 4) tends to $N(0,1)$ under the H_0 of a unit root. The row F-split shows the F-test statistic of the columns split against the fully restricted column (see section 5.2.2 for details). The $CIPS(p)$ test statistics are the cross section averages of the cross sectionally augmented Dickey-Fuller test statistics (Pesaran, 2007). The value list for the kurtosis is the moment. For the excess kurtosis subtract 3. The row labeled JB has the Jarque-Bera test statistic, which tends to $\chi^2(2)$ under the H_0 of normality. The R^2 for the CCEP estimations is the $\bar{R}^2_{CCEP}$ as defined in Holly et al. (2010).

* significant at 5%

** significant at 1%

Table F.4: Added 2nd difference for jobs, split per type of house

	added 2nd j		added 2nd j	
$p_{i,t-1}$	-1.32	(0.06)	-1.32	(0.06)
$y_{i,t-1}$	0.03	(0.19)	0.03	(0.19)
$\Delta p_{i,t-1}$	0.10	(0.03)	0.10	(0.03)
Δy_{it}	-0.10	(0.11)	-0.10	(0.11)
$g_{i,t-1}$	0.45	(0.17)	0.45	(0.17)
$h_{i,t-1}$	-0.07	(0.23)	-0.07	(0.22)
$j_{i,t-1}$	-0.37	(0.06)	-0.37	(0.06)
$\Delta j_{i,t-1}$ typ1			0.28	(0.07)
$\Delta j_{i,t-1}$ typ2			0.14	(0.04)
$\Delta j_{i,t-1}$ typ3			0.14	(0.04)
$\Delta j_{i,t-1}$ typ4			0.15	(0.04)
$\Delta j_{i,t-1}$ typ5			0.11	(0.05)
$\Delta j_{i,t-1}$	0.16	(0.03)		
r_{t-1}	-0.00		-0.00	
$\bar{p}_{t-1}$	1.27		1.28	
$\bar{y}_{t-1}$	0.07		0.07	
$\Delta\bar{p}_t$	0.92		0.92	
$\Delta\bar{p}_{t-1}$	-0.01		-0.01	
$\Delta\bar{y}_t$	0.10		0.10	
intp	-0.26		-0.26	
Derived				
γ	-0.02		-0.02	
ϕ	-1.32		-1.32	
Tests				
CD	3.64	**	3.45	**
IPS	NaN		NaN	
F-split			4.17	**
skewness	-0.34		-0.32	
kurtosis	7.92		7.88	
JB	2269	**	2226	**
R^2	0.89		0.89	

Notes: The columns show the results of the fixed effect and CCEP estimations. Standard errors are shown between brackets. For the CCEP estimation this is the Newey-West type standard error as defined in equation 74 in Pesaran (2006). The CD test statistic (Pesaran, 2004) tends to $N(0,1)$ under the H_0 of no cross-sectional dependence. The IPS test statistic (Im et al., 2003, section 4) tends to $N(0,1)$ under the H_0 of a unit root. The row F-split shows the F-test statistic of the columns split against the fully restricted column (see section 5.2.2 for details). The $CIPS(p)$ test statistics are the cross section averages of the cross sectionally augmented Dickey-Fuller test statistics (Pesaran, 2007). The value list for the kurtosis is the moment. For the excess kurtosis subtract 3. The row labeled JB has the Jarque-Bera test statistic, which tends to $\chi^2(2)$ under the H_0 of normality. The R^2 for the CCEP estimations is the $\bar{R}^2_{CCEP}$ as defined in Holly et al. (2010).
* significant at 5%
** significant at 1%

Table F.5: Added 2nd difference for jobs, split per type of living environment

	added 2nd j		added 2nd j	
$p_{i,t-1}$	-1.10	(0.06)	-1.11	(0.06)
$y_{i,t-1}$	0.47	(0.21)	0.47	(0.21)
$\Delta p_{i,t-1}$	0.03	(0.04)	0.03	(0.04)
Δy_{it}	0.15	(0.13)	0.15	(0.13)
$g_{i,t-1}$	0.73	(0.18)	0.74	(0.18)
$h_{i,t-1}$	-0.07	(0.24)	-0.07	(0.24)
$j_{i,t-1}$	-0.32	(0.08)	-0.32	(0.08)
$\Delta j_{i,t-1}$ typ1			0.16	(0.07)
$\Delta j_{i,t-1}$ typ2			0.16	(0.04)
$\Delta j_{i,t-1}$ typ3			0.24	(0.05)
$\Delta j_{i,t-1}$ typ4			0.17	(0.04)
$\Delta j_{i,t-1}$ typ5			0.14	(0.05)
$\Delta j_{i,t-1}$	0.17	(0.04)		
r_{t-1}	-0.00		-0.00	
$\bar{p}_{t-1}$	1.06		1.06	
$\bar{y}_{t-1}$	-0.39		-0.40	
$\Delta \bar{p}_t$	0.90		0.90	
$\Delta \bar{p}_{t-1}$	0.06		0.06	
$\Delta \bar{y}_t$	-0.14		-0.15	
intp	-0.20		-0.20	
Derived				
γ	-0.42		-0.43	
ϕ	-1.1		-1.11	
Tests				
CD	-0.81		-0.83	
IPS	-66.82		-79.06	
F-split			1.18	
skewness	0.1		0.09	
kurtosis	7.21		7.22	
JB	1618	**	1632	**
R^2	0.88		0.88	

Notes: The columns show the results of the fixed effect and CCEP estimations. Standard errors are shown between brackets. For the CCEP estimation this is the Newey-West type standard error as defined in equation 74 in Pesaran (2006). The CD test statistic (Pesaran, 2004) tends to $N(0,1)$ under the H_0 of no cross-sectional dependence. The IPS test statistic (Im et al., 2003, section 4) tends to $N(0,1)$ under the H_0 of a unit root. The row F-split shows the F-test statistic of the columns split against the fully restricted column (see section 5.2.2 for details). The $CIPS(p)$ test statistics are the cross section averages of the cross sectionally augmented Dickey-Fuller test statistics (Pesaran, 2007). The value list for the kurtosis is the moment. For the excess kurtosis subtract 3. The row labeled JB has the Jarque-Bera test statistic, which tends to $\chi^2(2)$ under the H_0 of normality. The R^2 for the CCEP estimations is the $\bar{R}^2_{CCEP}$ as defined in Holly et al. (2010).

* significant at 5%

** significant at 1%

Appendix G

Common Correlated Effect Pooled estimator

This section shows the Common Correlated Effect Pooled (CCEP) estimator as developed in Pesaran (2006). This method can be used to get coefficient estimations for panel data that exhibit cross-sectional dependency. The CCEP estimation is free from bias that the cross-sectional dependency can cause in regular fixed effect estimations.

It is assumed that the cross-sectional dependency is caused by a number of unobserved common factors. These factors are unobserved but are also present in the cross section averages. The cross section averages are, for a variable the average value between individuals, for each time. These time series can be used as proxies for the unobserved common variables. By adding these to the model, each with a coefficient that can vary per individual, the cross-sectional dependency is "removed" from the system.

Following are the formulas that describe the estimation. The weights that are used in Pesaran (2007) are assumed to be all equal as in Holly et al. (2010). As before, N is the number of individuals, T the number of time steps, and k the number of observed variables. Let the vectors

$$\mathbf{z}_{it} = \begin{pmatrix} p_{it} \\ \mathbf{x}_{it} \end{pmatrix} \tag{G.1}$$

be the combination of regressand and observed variables, and let

$$\bar{\mathbf{z}}_t = \frac{1}{N}\sum_{i=1}^{N}\mathbf{z}_{it} \tag{G.2}$$

be the time series of the cross section averages of these. Then

$$\bar{\mathbf{H}} = (\tau_T, \bar{\mathbf{Z}}) \tag{G.3}$$

is the $T \times (k+2)$ matrix with the T observations of the cross section averages, augmented with τ_T, a $T \times 1$ vector of unity. Then the matrix

$$\bar{\mathbf{M}} = \mathbf{I}_T - \bar{\mathbf{H}}(\bar{\mathbf{H}}'\bar{\mathbf{H}})^{-1}\bar{\mathbf{H}}' \tag{G.4}$$

can be used to "remove" the common effects from variables. Further, let

$$\mathbf{X}_i = (\mathbf{x}_{i1}, \mathbf{x}_{i2}, \ldots, \mathbf{x}_{iT})' \tag{G.5}$$

be the matrix with the observations of the explanatory variables for i.

With these two estimators for coefficients can be constructed. First the *mean group* estimator. For this one, the coefficients are estimated for each individual separately. The mean of these individual coefficients is then used:

$$\hat{\mathbf{b}}_i = (\mathbf{X}_i'\bar{\mathbf{M}}\mathbf{X}_i)^{-1}\mathbf{X}_i'\bar{\mathbf{M}}\mathbf{p}_i, \tag{G.6}$$

$$\hat{\mathbf{b}}_{CCEMG} = \frac{1}{N}\sum_{i=1}^{N}\hat{\mathbf{b}}_i. \tag{G.7}$$

The second estimator is the *pooled* estimator, where the assumption of the coefficient being equal for all individuals is used to improve the efficiency:

$$\hat{\mathbf{b}}_{CCEP} = \left(\sum_{i=1}^{N}\mathbf{X}_i'\bar{\mathbf{M}}\mathbf{X}_i\right)^{-1}\sum_{i=1}^{N}\mathbf{X}_i'\bar{\mathbf{M}}\mathbf{p}_i. \tag{G.8}$$

The CCEP estimation of equation G.8 is reported to work better and has been used in this research.

Pesaran derived the variance of the CCEP estimator as:

$$\widehat{\text{Var}}(\hat{\mathbf{b}}_{CCEP}) = N^{-1}\hat{\Psi}^{*-1}\hat{\mathbf{R}}^{*}\hat{\Psi}^{*-1} \tag{G.9}$$

where

$$\hat{\Psi}^{*} = \frac{1}{NT}\sum_{i=1}^{N}\mathbf{X}_i'\bar{\mathbf{M}}\mathbf{X}_i \tag{G.10}$$

and,

$$\hat{\mathbf{R}}^{*} = \frac{1}{N-1}\sum_{i=1}^{N}\left(\frac{\mathbf{X}_i'\bar{\mathbf{M}}\mathbf{X}_i}{T}\right)\left(\hat{\mathbf{b}}_i - \hat{\mathbf{b}}_{CCEMG}\right)\left(\hat{\mathbf{b}}_i - \hat{\mathbf{b}}_{CCEMG}\right)'\left(\frac{\mathbf{X}_i'\bar{\mathbf{M}}\mathbf{X}_i}{T}\right) \tag{G.11}$$

The alternative uses a Newey-West type correction for correlation and heteroskedasticity. The variance of the estimator is then given by:

$$\widehat{\text{Var}}(\hat{\mathbf{b}}_{CCEP}) = T^{-1}\hat{\Psi}^{*-1}\left(\sum_{i=1}^{N}\hat{\mathbf{S}}_{i\varepsilon}\right)\hat{\Psi}^{*-1}, \tag{G.12}$$

where

$$\hat{\mathbf{S}}_{i\varepsilon} = \hat{\Lambda}_{i0} + \sum_{j=1}^{p}\left(1 - \frac{j}{p+1}\right)(\hat{\Lambda}_{ij} + \hat{\Lambda}_{ij}'), \tag{G.13}$$

$$\hat{\Lambda}_{ij} = T^{-1}\sum_{t=j+1}^{p}\tilde{e}_{it}\tilde{e}_{i,t-j}\hat{\mathbf{x}}_{it}\hat{\mathbf{x}}_{i,t-j}', \tag{G.14}$$

and

$$\tilde{e}_{it} = \bar{\mathbf{M}}(\mathbf{y}_i - \bar{\mathbf{X}}_i\hat{\mathbf{b}}_{CCEP}). \tag{G.15}$$

A practical advantage of the estimator in G.12 is that it does not rely on the mean group estimations for $\hat{\mathbf{b}}_i$. For the model used in this research these estimations failed in some cases due to the matrix $\mathbf{X}_i'\bar{\mathbf{M}}\mathbf{X}_i$ being singular. Therefore the variance as given by equation G.12 was used to calculate standard errors for the coefficients.

An implementation in GAUSS of the estimators for the coefficients and variances is available from the authors of Pesaran (2006)[1]. For this research this code was used as a reference to implement the estimations within the plm package (Croissant and Millo, 2008) in R (R Development Core Team, 2011).

[1] http://www.econ.cam.ac.uk/faculty/pesaran/ppfiles/CCEgauss6_22Aug08.zip

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