TRANSPORT INFRASTRUCTURE CAPITAL EFFECTS AND REGIONAL SPILLOVER IN FINLAND

Aino Pauliina Krigsholm

University of Helsinki

Faculty of Social Sciences

Economics

Master's Thesis

February 2016

HELSINGIN YLIOPISTO
HELSINGFORS UNIVERSITET
UNIVERSITY OF HELSINKI

Faculty	Department
Faculty of Social Sciences	Department of Political and Economic Studies

Author
Aino Pauliina Krigsholm

Title
Transport Infrastructure Capital Effects and Regional Spillover in Finland

Subject
Economics

Level	Month and year	Number of pages
Master's thesis	February 2016	69 + 1

Abstract

The effects of public capital on economic growth have been widely examined in empirical studies during the past few decades. This thesis analyses the dynamic effects of transport infrastructure capital, a subgroup of public capital, in Finland on two levels of geographic hierarchy. Using both national and regional dimensions in the analysis allows the evaluation of the spillover effects that public investments in transport infrastructure are suggested to produce according to earlier literature.

In this thesis, the impact of transport infrastructure capital on regional growth is studied within the multivariate time series framework. The important issues of the non-stationarity of the data and the existence of cointegrating relationships among variables in the long-run can be accounted for by using vector autoregressive (VAR) models. Moreover, the VAR approach does not impose any causal links between the variables a priori. This is particularly important in the context of this thesis since it is plausible to assume that shocks hitting output affect public capital spending and, therefore, also the level of transport infrastructure capital stock.

For the estimation of direct transport infrastructure capital effects with the VAR approach four variables are used: the real gross domestic output produced, employment in number of workers, the net private non-residential capital stock, and the net transport infrastructure capital stock. All the series are for the period 1975—2004 and in year 2000 prices. In addition, for the purpose of evaluating the spillover effects, I estimate so-called effective transport infrastructure capital stock series that consist of inside-region and outside-region capital stocks for each region.

The main empirical results of this thesis are based on the impulse response functions associated to the VARs estimated for Finland as a whole and for each Finnish region. The empirical results suggest that in Finland and in the majority of regions, the effects of transport infrastructure capital are negative. The negative responses of all other variables to a shock to the transport infrastructure capital variable indicate that private sector variables are substitutes to transport infrastructure capital. On regional level the estimated long-run elasticities are in general lower than the national level elasticities, implying the existence of negative spillover effects.

My empirical results are in part contradictory to many previous studies, yet the response patterns are explicable in terms of economic theory. Assuming that the neoclassical production function is a valid representation of the relationship between the variables used, my results suggest that the marginal productivity of transport infrastructure capital is negative, which in turn implies that the transport infrastructure to output ratio is beyond its optimal level in most parts of Finland.

Keywords
transport infrastructure capital, regional spillover, vector autoregression, cointegration, impulse response analysis

HELSINGIN YLIOPISTO
HELSINGFORS UNIVERSITET
UNIVERSITY OF HELSINKI

Tiedekunta/Osasto	Laitos
Valtiotieteellinen tiedekunta	Politiikan ja talouden tutkimuksen laitos

Tekijä
Aino Pauliina Krigsholm

Työn nimi
Transport Infrastructure Capital Effects and Regional Spillover in Finland

Oppiaine
Taloustiede

Työn laji	Aika	Sivumäärä
Pro gradu	Helmikuu 2016	69 + 1

Tiivistelmä

Julkisen kiinteän pääoman vaikutuksia alueiden talouskasvuun on tarkasteltu monissa empiirisissä tutkimuksissa jo useamman vuosikymmenen ajan. Tässä työssä keskitytään tarkastelemaan liikenneinfrastruktuuripääoman, yhden julkisen kiinteän pääoman alaryhmän, dynaamisia vaikutuksia Suomessa koko maan sekä maakuntien tasolla. Aiempien tutkimusten mukaan julkiset investoinnit liikenneinfrastruktuuriin saattavat synnyttää taloudellisia vaikutuksia yli alueellisten rajojen. Kahden eri maantieteellisen tason huomioiminen mahdollistaa tällaisten alueellisten vuotovaikutusten tarkastelun.

Tässä työssä liikenneinfrastruktuuripääoman vaikutusten arvioimiseen käytetään usean muuttujan aikasarjamalleja. Tällöin sekä muuttujien epästationaarisuuteen että muuttujien välisiin yhteisintegraatiosuhteisiin liittyvät seikat on mahdollista ottaa huomioon mallintamisessa. Vektori autoregressiivisten (VAR) mallien käyttämistä puoltaa myös se, että menetelmä ei lähtökohtaisesti aseta minkäänlaisia olettamuksia muuttujien välisistä kausaalisista yhteyksistä. Kaksisuuntaisen kausaalisuuden mahdollisuus ei ole missään nimessä poissuljettu tässä yhteydessä, koska oletettavasti kokonaistuotantoon kohdistuvat shokit vaikuttavat myös julkisen pääoman menoihin ja sitä myöten liikenneinfrastruktuuripääoman määrään.

Liikenneinfrastruktuuripääoman suorien vaikutusten estimointia varten työssä käytetään neljää muuttujaa: alueellista tuotosta bruttokansantuotteella mitattuna, työllisyyttä työntekijöiden lukumäärällä mitattuna, yksityistä pääomakantaa sekä liikenneinfrastruktuuripääomakantaa. Kaikki aikasarjat ulottuvat vuosille 1975—2004 ja ne esitetään kiinteähintaisina vuoden 2000 hinnoin. Alueellisten vuotovaikutusten tarkastelua varten työssä estimoidaan lisäksi maakuntien sisäisestä sekä ulkoisesta liikenneinfrastruktuuripääomakannasta muodostuvat, niin kutsutut tehokkaat liikenneinfrastruktuuripääomakannat kaikille Suomen maakunnille.

Impulssivastefunktiot muodostavat työn tärkeimmät empiiriset tulokset. Tulosten mukaan koko maan tasolla sekä valtaosassa maakuntia liikenneinfrastruktuuripääoman vaikutukset ovat negatiivisia. Kaikkien muiden muuttujien negatiivinen vaste liikenneinfrastruktuuripääomaan kohdistettavaan shokkiin viittaa siihen, että lisäys liikenneinfrastruktuuripääomaan syrjäyttää tuotantoa, työllisyyttä sekä yksityistä pääomaa. Työssä estimoitavat pitkän aikavälin joustot ovat keskimäärin alhaisempia maakuntien kuin koko maan tason tasolla. Tämä havainto viittaa negatiivisten alueellisten vuotovaikutusten olemassaoloon.

Työn empiiriset tulokset ovat osittain ristiriidassa aiempien tutkimusten kanssa, mutta impulssivastefunktioiden muotoa pystytään selittämään talousteorian kautta. Olettaen että neoklassinen tuotantofunktio kuvaa edustavasti muuttujien välisiä yhteyksiä, tulokset antavat ymmärtää että liikenneinfrastruktuuripääoman rajatuottavuus on negatiivinen, mikä puolestaan viittaisi liian korkeaan liikenneinfrastruktuuripääoman määrään suhteessa tuotantoon suuressa osassa maata.

Avainsanat
liikenneinfrastruktuuripääoma, alueellinen vuotovaikutus, VAR, yhteisintegraatio, impulssivasteanalyysi

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1 Introduction

The role of transport infrastructure in a regional economic development - and in an economy as a whole - can be described as a spatial phenomenon. Transport infrastructure functions as a network connecting different regions together. Therefore a change in productivity in one region can be a consequence of reduction in transport costs in its own region or, alternatively, it can be caused by an increase in accessibility to other regions. Considering the spatial dependence is thus necessary in order to capture the broad regional impacts of infrastructural improvements, including both the local and spillover effects, on economic output. (Chen & Haynes, 2015.)

In this thesis, the scope is on evaluating to what extend Finland as a whole and each of its regions individually respond to changes in transport infrastructure capital stock. By comparing national and sub-national level results it is possible to examine whether the suggestion that responds are milder on lower level of spatial hierarchy holds. Moreover, I evaluate if regional spillovers exist, meaning that output in a particular region is affected by investments in transport infrastructures in other regions of the country.

Similar to recent evidence on income convergence that it is possible for convergence to take place at one level in a spatial hierarchy and divergence at another level, also transportation investment may be considered to have such outcomes. A vast literature (Munnell, 1990; Boarnet, 1998; Márguez et al., 2011, to mention few) suggests that for public capital and private output, the output elasticities on different spatial levels differ from each other. Notably the estimated impact of public capital becomes smaller as the geographic focus narrows. Naturally this can be explained by positive spillover effects; one should look at larger geographic area in order to capture all of the payoff to an infrastructure investment. Respectively it can be argued that capturing negative spillover effects such as reallocation of economic activity requires small enough geographical scope (Boarnet, 1998). My empirical results using Finnish data on national and regional level support the prediction of smaller estimated impact on lower level of spatial hierarchy and, therefore, also the existence of regional spillovers. In addition, the results that I obtain show that substantial regional disparities exist when the transport infrastructure effects are quantified as long-run elasticities.

Among many others, Banister and Berechman (2003) divide the effects of infrastructural improvements into direct and indirect ones. Direct effects appear via reduction in transport costs. As a factor of production of goods and services, transport represents a cost to individual firms. Hence reducing costs of transportation enables firms to lower their prices, which in turn should, according to traditional economic logic, enhance demand and production of the firms.

Moreover, individual households benefit from lower travel costs. Indirect effects originate from improvements in accessibility. Often these effects are called external benefits or wider economic impacts. Better accessibility may improve operational preconditions as well as increase firm's productivity. In addition, benefits may include employment generation, increased availibility of labour and changes in land and property values. (Banister & Berechman, 2003.)

In macro-level the absence of a well-developed transport infrastructure can be seen as a constraint to growth. Indisputably the need for mobility of economic resources and goods generates requirement for (extensive) transport networks. Especially in developing countries the establishment of new transport links has according to case studies (see e.g. Calderón & Servén, 2004a) repeatedly yielded positive impact on economic development. In more developed countries the evidence is less clear, presumably due to smaller relative changes in transport costs. Furthermore, improvements on single node of the network are less crucial in an economy where exists alternative transportation modes. To summarize, the intensity of the impacts depends largely on the quantity and quality of the existing infrastructure, its geographical layout and the level of economic development (Álvarez-Ayuso et al., 2014).

One of the most interesting questions about relationship between transport infrastructure and economic development scales down to regional level. According to Ivanova (2003), in regional level context infrastructural improvements can be seen as a way to remove barriers to trade with other regions. By improving a transport link a region is able to start using regional resources such as land and labor more efficiently. Through this shift there is a positive impact on region's productivity. Moreover, poor transport connections may protect fairly uncompetitive firms within the region. Thus increased competition due to infrastructural improvements can also improve efficiency on some sectors.

The school of New Economic Geography (NEG) also emphasises the role of transport costs as a location factor. In contrary to classical trade theory, NEG models are build within the context of imperfect competition, increasing returns to scale and different degrees of interregional labour mobility (Fujita et al., 1999). The so-called core-periphery model by Krugman (1991) underlines the connection between transport costs and the degree of production agglomeration. According to this model, lower transport costs alongside with economies of scale and a higher manufacturing share, tend to shift production from agricultural "periphery" to industrialized "core" area. However, for example Kilkenny (1998) has examined that eventually, as nominal wages paid to workers grow at the core, the concentration turns into geographical dispersion. This implicates the existence of some critical level of transport costs in this setting, after which the production starts to disperse and the wages to converge.

In theory, transport infrastructure influences economy on micro-, macro- and regional levels. The empirical evidence is, however, quite ambiguous. Aschauer (1989) started a branch of studies focusing on relationship between public investment (including transport infrastructure) and economic development. The earliest estimates (Aschauer, 1989; Munnell, 1990) suggest that through its contribution to technical change, transport infrastructure is a significant source of economic growth. Surely there exists a strong correlation between the level of investments in infrastructure (road infrastructure in particular) and the levels of economic indicators such as GDP per capita, but this observation alone does not define the direction of the cause-effect relationship. Furthermore, empirical studies (Holtz-Eakin, 1994 for example) point that it is much harder to explain changes in economic indicators, i.e. economic growth and decline, by transport investment. Holtz-Eakin (1994) even states that the best estimate of the elasticity of private output or productivity with respect to state and local government capital is essentially zero. My empirical results lean more towards the statement of Holtz-Eakin (1994). In fact, my results suggest that increases in transport infrastructure capital crowd-out private sector variables both in short-run and in long-run. Some regions show positive responses to a shock to transport infrastructure capital but for majority of regions the output, employment as well as private capital responses are negative.

This thesis is constructed as follows. Section 2 reviews the literature of transport infrastructure capital and economic development. Previous studies are categorized into studies that focus especially on the regional spillover effects (Ch 2.2) and into those that do not (Ch 2.1). Section 3 includes data description as well as some descriptive statistics on regional development of variables. In Section 4 I focus on chosen aspects of multivariate time series methodology and in Section 5 I present results of my empirical analysis. Finally, in Section 6 concluding remarks are made.

2 Literature Review

2.1 Studies on Transport Infrastructure and Economic Development

An expanding literature has examined the channels through which infrastructure might affect economic growth. Oosterhaven and Knaap (2003) provide a good overview of economic models which investigate the issue especially on regional level. They note that "the basic problem lies in establishing the economic development that would have occurred without the investment in infrastructure". Also the uncertainty about the direction of the impact of new transport infrastructure on the regions or nations adds some more challenge to empirical research. Despite the modeling issues, empirical literature has produced some general qualitative outcomes. First of all, it appears that regardless the choice of modeling technique, models show the same spatial pattern of impacts of infrastructure. Second, it is clear that level of impacts depends greatly on the total level of infrastructure that country has. That is, new infrastructure produces small impacts in countries with abundant infrastructure services. (Oosterhaven & Knaap, 2003.)

Economic effects of infrastructure improvements are mainly connected to a perceived reduction in transport costs. From microeconomical perspective, it is convenient to use the incremental *social surplus* as a welfare measure. A cost benefit analysis (CBA) is the most widely used tool for measurement and valuation of the social surplus. A common viewpoint is, however, that the CBA's ability to capture economic development impacts is limited. Macro-oriented studies using a production function approach (for example Aschauer, 1989; Munnell, 1990) aim to assess also the 'wider' benefits including the spillover effects that were not assumed to be captured by the CBA. In addition to production function approach, econometric analysis of the topic has been performed with national and regional growth approaches that focus on multiplier effects of public infrastructure. (Oosterhaven & Knaap, 2003.)

Empirical research about the role of public capital in economic growth can be categorized considering at least following perspectives: (1) the definition and scope of public capital, (2) the division between country and regional level studies, (3) the main approaches (production functions, cost functions and vector autoregressive (hereafter VAR) models), and (4) the level of aggregation of the data (all sectors or specific sectors). I use approach-based categorization in this chapter. However, also the other perspectives are acknowledged in what follows. I will present some empirical results achieved with any of the three approaches. The emphasis is though on VAR approach studies, since the empirical part of this thesis shall be conducted using VAR models.

2.1.1 Production function approach

Macro- and regional level evaluation of infrastructure and its impact on growth and productivity typically has been done with production function approach. The approach rests upon estimation of production functions for different sectors in a region as functions of different input factors. Much of the literature examines the growth effects of public investment rather than infrastructure. Transport infrastructure is then included as a public input factor used by firms within the region. The story goes that regions with higher levels of infrastructure provision will have higher output levels and, also, regions with efficient and abundant transport infrastructure will produce more transport-intensive goods. Evidently the production function approach does not pay any attention to the network properties of transport infrastructure. This is one of the reasons why the econometric estimation tends to confound rather than clarify the causal relationships and substitution effects between input factors. (Bröcker, 2001.)

In regression estimations the dependent variable is usually output within some area, and the explanatory variables typically include private and public capital, labour and a constant for the level of technology[1] (Munnell, 1992). Generally in such regressions, the levels of public capital are found (highly) significant. Aschauer's (1989) seminal paper presents that the 'core' infrastructure of streets, highways, airports, mass transit, sewers, water systems, et cetera, has most explanatory power for productivity, compared to military spending and other types of non-military spending.

Many of the early results have been criticised for producing implausibly large economic significance for the stock of public infrastructure capital. Later studies applying the same methodology to international, regional and sectoral data mainly failed to replicate such large effects of aggregate public capital on private output. This is mostly due to use of 'unsophisticated' econometric techniques to current standards, or to put it more precisely ignoring time and state effects as well as non-stationarity in time series approaches. Criticism towards macro productivity models has been summarized with some key elements (Bråthen, 2001). First, there may be problems with the breakdown of public capital into different kinds of transport infrastructure. Two methods exist, the 'reconstruction cost approach' and the 'market value approach', and as an example, for a scarcely used high quality infrastructure the market value

[1] Formally we have $Q = A * f(K, L, G)$, where Q is output, A the level of technology, K the private capital stock, L labour and G the stock of public capital. Assuming a generalized Cobb-Douglas form and taking logarithms produces a linear function that can be estimated: $lnQ = lnA + a \cdot lnK + b \cdot lnL + c \cdot lnG$. Now the coefficients a, b, and c are the output elasticities of factor inputs and they indicate the percentage change in output for a given percentage change in factor input.

will most likely be lower than it's value based on reconstruction costs. Second, only few authors have paid attention to mode specific productivity effects. Most studies instead comprise one variable for transport infrastructure. Third, in general it is very challenging to try to determine the elements that influence private sector productivity. Both investment activity in other sectors and the composition of the consumption bundle may have a significant impact, and that of course dilutes the reliability of the regression estimations. Finally, Bråthen (2001) points out that the public capital variable must be exogenous to the economy for the analysis to become valid. (Bråthen, 2001.)

To obtain more evidence, Munnell (1990) studied the relationship between public capital and measures of economic activity in US at the state level. After estimating production functions for states she found that though public capital had a positive impact on output, the output elasticity was approximately half the size of the national-level estimate. Overall Shatz et al. (2011) present that studies of highway infrastructure using a national-level data are more likely to find a positive and significant relationship between infrastructure and economic development than studies using state- or regional-level data. Shatz et al. (2011) argue that this may be explained by the tendency of highway infrastructure to reallocate economic activity. In light of this explanation, it requires a smaller geographic scale than national-level to obtain negative spillover effects. Also Boarnet (1998) has examined the possible negative spillover effects from public infrastructure in linear production function framework. He concludes that changes in county output are positively associated with changes in street and highway capital within the same county, whereas output changes are negatively associated with capital changes in other counties.

Taking into account both quantity and quality of infrastructure, Calderón and Servén (2004b) explore the effects of infrastructure on growth and distribution using a large panel data set comprising 121 countries and spanning the years 1960-2000. Their focus is on examining long-run trends in growth and inequality rather than their behaviour over the business cycle. Furthermore, instead of focusing on one single infrastructure sector, they build synthetic indices that summarize various dimensions of infrastructure and its quality. To deal with endogeneity issues, Calderón and Servén (2004b) use a variety of generalized method of moments (GMM) estimators based on both internal and external instruments. The coefficient estimate of the infrastructure is still found positive and significant even after including these instruments.

Also Canning and Pedroni (2008) investigate the consequences of various types of infrastructure provision in a panel of countries from 1950 to 1992. The infrastructure data gives physical infrastructure measured on annual basis, and transport infrastructure is measured in kilome-

ters of paved road. The presence of unknown heterogeneous short-run causal relationships is taken into account by using cointegration tests[2] . Canning and Pedroni (2008) base their approach on the endogenous growth model of Barro (1990) that includes tax-financed government services (such as infrastructure) that affect production or utility. Thus in their approach exists an optimal level of infrastructure which maximizes the growth rate[3]. Too high level of infrastructure is expected to divert investment away from other capital to the point where income growth starts to reduce. Their results indicate that in general both short-run and long-run causality is bi-directional, with infrastructure responding to GDP per capita but GDP per capita also responding to infrastructure shocks. Though infrastructure does tend to cause long-run economic growth, there is clear variation across countries. According to their studies, supply of infrastructure seems to be too low in some countries while in others it is too high. This suggests that the appropriate policy at the country level depends on country-specific studies.

2.1.2 Cost function approach

Production function approach has been criticised for being inaccurate due to the restrictions it places on technology and a firm's behavior, as well as "its failure to take into account private input prices which would affect the intensity of their use" (Moreno et al. 2000). These problematics may be tackled by using the cost function approach. Basically the cost function approach evaluates whether costs decrease with public capital provision. The estimation of cost and profit functions, often called *the duality theory*, considers explicitly the optimizing behavior of firms with respect to inputs, and prices are the only exogenous variables. (Nadiri & Mamuneas, 1994; Moreno et al., 2002.)

Moreover, compared to production function studies that usually assume the Cobb-Douglas form (which imposes restrictive conditions of the substitutability of inputs), cost functions provide more flexible functional forms. Using the cost function yields direct estimates of the various elasticities of substitution, which allows for examining the pattern and degree of complementarity and substitutability among the factors of production (relationship between

[2]Two non-stationary time series variables, lets denote them $x_t \sim I(1)$ and $y_t \sim I(1)$, are said to be cointegrated if there exists linear combination of them that is stationary, i.e. $z_t = ax_t + by_t \sim I(0)$. The issue of modeling non-stationary variables is discussed in more detail in Chapter 4 of this thesis. In Canning and Pedroni (2008), according to cointegration tests (Augmented Dickey-Fuller test), there is cointegration between each infrastructure variable and GDP per capita. In other words, results suggest that there exists a long-run relationship between infrastructure and income.

[3]Barro (1990) shows that the welfare-maximizing level of productive expenditure is the same which maximizes the economy's growth rate. Actually it is achieved when the share of productive government expenditure in GDP equals the elasticity of aggregate output with respect to the same variable.

private and public factors). Also the marginal benefit of infrastructure capital can be easily derived from a cost function, since it is simply the first derivative of cost with respect to public capital. The sign of the cost derivative with respect to infrastructure capital indicates the direction of the effect: A negative sign points that an additional unit of public capital stock will benefit the firm, whereas a positive sign addresses the opposite. Required data on input prices are not, however, easily available, which makes the cost function approach less popular than the production function approach. (Moreno et al., 2002.)

Nadiri and Mamuneas (1994) studied the effects of publicly financed infrastructure and R&D capitals on the cost structure and productivity performance of twelve U.S. manufacturing industries. They found significant positive effects for both capital types. They note, however, that the effects on cost structure for different industries seems to vary a lot. According to Nadiri and Mamuneas (1994), public capital services affect the cost structure of an industry in two ways. First one, called the productivity effect, implies that in an industry a larger quantity or better quality of public capital services shall move the cost per unit of output downward if the industry receives any benefit from improved public capital services. Second, depending on whether public capital services are substitutes or complements of the factors of production in the private sector, firms will adjust their demand for labour, intermediate inputs and physical capital stock. (Nadiri & Mamuneas, 1994.)

Moreno et al. (2002) remark that most cost function studies focus on the direct effect of public capital which can be distinguished through changes in variable costs. The indirect influence deriving from changes in the requirement of private capital remains, however, less examined. Moreno et al. (2002) extend the cost function approach to a consideration of the effects of infrastructure on the optimal amount of private capital. They measure the long-run effects of infrastructure through private capital adjustments. Private capital is described as 'quasi-fixed' input which can be adjusted in the long-run in response to changes in public capital. Applying this approach Moreno et al. (2002) argue that an improvement in the endowment of public capital can basically have twofold effects: (1) a short-run effect due to cost reductions in variable inputs as a consequence of the new public capital stock while the economy is constrained by its current private capital stock, and, (2) a long-run effect stemming from a higher infrastructure endowment that in turn changes a firm's desired level of private capital. (Moreno et al., 2002.)

2.1.3 Multivariate time series framework

Empirical studies on the subject based on VAR models have gained popularity in recent years. VAR models do not place such restrictions on the interaction between output, public capital, and private capital, as structural approaches do. Overall, the VAR approach has several advantages over structural approaches. Kamps (2005) distinguishes the advantages followingly: (1) The VAR approach does not impose any causal links between model variables *a priori*. Instead, one of the goals is to test whether the causal relationship implied by the production function approach is valid or whether there are feedback effects from output to the inputs. (2) Also the indirect links are perceived with VAR approach. Consequently, the long-run output effect of a chance in public capital results from the interaction of the model variables. This means that public capital may not only directly affect output but may also have an indirect impact on output via its effects on the private factors of production. (3) The VAR approach allows for more than one long-run (cointegration) relationship among the model variables. It is possible to explicitly test for the cointegration rank and impose it in the estimation of the VAR model. (Kamps, 2005.)

Making comparisons between results of different VAR approach studies is by no means straightforward. This is primarily because the econometric techniques used vary, which makes similar terms such as output elasticity and marginal product of public capital not always comparable. Moreover, if public investment is considered as an exogenous variable (as in most studies it is), the dynamic feedback effects among the relevant variables cannot be taken into account. However, this does not prevent us from trying to draw some general conclusions from previous studies.

Many studies specify VAR models in first differences without testing for cointegration (see for example Pereira, 2000; Pereira & Roca-Sagales, 2001). This seems unrational since first-differentiating neglects potential long-run relationships between the levels. Some authors specify VAR models in levels instead. This approach is usually validated by the result of Sims, Stock and Watson (1990) that OLS estimates of VAR coefficients are consistent even if the variables are non-stationary and possibly cointegrated. However, as Kamps (2005) remarks, the consistency of VAR coefficient estimates does not extend to estimates of impulse response functions.

Crowder and Himarios (1997) were among the first ones to use a multivariate time series approach for analysing the relationship between output, the private capital stock and the public capital stock. They found results that support Aschauer's (1989) claim that public capital is at the margin more productive than private capital. Instead of the 'traditional'

attempts to estimate restrictive production functions, they exploit the so-called *balanced growth restrictions* implied by neoclassical growth models that include the government capital stock in the production function. They use the Johansen (1988) method to test for the common trend in the data implied by balanced growth. Moreover, they examine the relationship of public capital to private output in a way that there should be no problems with spurious regression. They remove the common trend from series of each variable and use the stationary deviations from the common trend to estimate output elasticities. These estimates are then compared with estimates from previous studies.

In Crowder and Himarios (1997), the balanced growth restrictions are used to provide guidance in the normalization of the cointegration vectors. They argue that these restrictions from an equilibrium model imply two cointegration vectors among the three variables (private capital, public capital and output), and one common stochastic trend among the variables. According to Crowder and Himarios (1997), it would be improper to use the cointegration methodology to estimate the production function since no long-run steady state restrictions are implied by the production function itself. They estimate the linearised Cobb-Douglas version of the representative production function using OLS and come to a conclusion that, under constant returns to scale (CRS) assumption, public capital is slightly more productive at the margin as private capital. Nevertheless, the elasticity estimates are found to be much smaller than those obtained by Aschauer (1989).

Pereira (2000) uses a VAR approach to investigate the effects of public investment on private sector performance in the US. Estimation results in this study suggest that all types of public investment have a positive effect on private output. Pereira (2000) especially argues that dynamic feedbacks are important to a conceptual understanding of the relationship between public capital and private sector performance. In theory, indeed public capital can have both direct effects as an additional input in the production function and indirect effects via private inputs, capital, and labour. One should also note that a greater availibility of public capital could reduce the demand for private inputs (substitution effect) as well as increase the marginal productivity of private inputs and in turn lower the marginal costs of production and potentially increase the level of private production (scale effect). Furthermore, Pereira (2000) reminds that there is a real possibility that private output and private inputs may be leading the evolution of public capital, and with VAR approach this can also be examined.

In his analysis Pereira (2000) points out that for the determination of the effects of public investment on the private sector variables, the critical issue is the identification of shocks to public capital that are not contemporaneously correlated with shocks in the private sector variables. In an ideal situation a researcher would know what fraction of investment decisions is

due to purely non-economic reasons. Pereira (2000) explains that the econometric counterpart of this idea could be a policy function that relates the rate of growth of public investment to the information in the relevant information set (for example, the past and current observations of the growth rates of the private-sector variables). Then the residuals from this policy function would represent the unexpected component to public investment, which are uncorrelated with other innovations. When estimating the effects of shocks to the different types of public investment on private output, private investment and employment, Pereira (2000) found that infrastructure investment yielded the weakest effect on all of the variables. This is of course in contrary to Aschauer's (1989) results that core infrastructure investment in highways has the highest effect on private output.

Pereira and Roca-Sagales (2001) conduct analysis on the effects of public capital formation on private sector performance both at the aggregate level and the disaggregated sectoral level in Spain. At the aggregate level it seems that public capital crowds in private inputs and also has positive effects on private output. Moreover, they suggest that the magnitude of the (positive) effects of public capital formation varies between sectors. Given the nature of public capital as a public good, Pereira and Roca-Sagales (2001) present a guess that the sum of the sectoral estimates of marginal products should be roughly equal to the marginal product obtained from the aggregate estimates. In absolute terms, the service sector seems to gain the most. Private capital reacts positively for all sectors but agriculture, indicating that public capital formation and private investment are complements. The sector of services captures clearly larger share of the effects of public capital on private capital accumulation that its share of the private capital stock is. Therefore it seems that public capital formation tends to bias the allocation of private capital, favoring the sector of services.

The effects of public capital formation on labour seem instead to be biased towards construction sector. Also manufacturing gets a relatively large share of the jobs created by public investment. So the results imply that in the case of Spain, public capital formation shifts the sector allocation of employment away from agriculture and services towards manufacturing and construction. Similarly it seems that, at the margin, construction and manufacturing benefit disproportionately in terms of output. In other words, it seems that public investment shifts the composition of output towards these two sectors. (Pereira & Roca-Sagales, 2001.)

Kamps (2005) provides internationally comparable results by estimating the dynamic effects of public capital using the VAR methodology for a large set of OECD countries. The study builds on new estimates of real government and private net capital stocks for 22 OECD countries for the 1960-2001 period. The capital stocks are estimated using the so-called perpetual inventory method that builds on a standard capital accumulation equation. According to

Kamps (2005), in majority of examined countries the long-run elasticity of output with respect to public capital is positive. In the case of Finland, the long-run elasticities of private capital, employment and real GDP are estimated to be 0.68, 0.50 and 0.72, respectively. These results indicates that public capital should be productive in Finland.

A regional aspect was not present very often in earlier VAR approach studies. During recent years, however, several authors have analysed the impact of public capital on regional growth using the multivariate time-series frameworks based on VAR models. For example Márguez et al. (2011) measure the effects of public capital for 17 regions in Spain using a structural VAR approach. They consider the dynamic effects from a 'domestic' perspective, meaning that only the effects derived from public capital installed in the region itself are taken into account. Methodologically their study differs from many others since they apply panel integration and cointegration techniques to analyse the long-run determinants of regional growth processes. Moreover, to produce consistent estimates of impulse responses, Márguez et al. (2011) embed the long-run cointegration function within the structural vector error correction short-run models. (Márguez et al., 2011.)

The results of Márguez et al. (2011) obtained both positive and negative domestic effects from public capital. Overall, there seems to be a significant geographical pattern in responses of regional private capital, employment and output to innovations in public capital located in the region itself. Short-run output response was significant and positive for nine regions (out of seventeen), significant and negative for four regions, as well as non-significant for four regions. Márguez et al. (2011) explain negative short-run output responses by substitution effect, since it seems that for certain regions public capital crowds out both private capital and employment. The long-run output responses show quite similar pattern. The responses were significant and positive in seven cases, significant and negative in four cases, and non-significant in six cases. As in general, the results indicate that public capital is productive for most regions. However, all the significant and positive short- and long-run elasticities were smaller than one, and especially the estimates for private capital elasticities were inconclusive. (Márguez et al., 2011.)

In order to develop the regional analysis a little further, Márguez et al. (2011) consider the spatial dimension of estimated effects by using an exploratory spatial data analysis approach. They point out that for the case of the long-run effects of public capital on private capital there seems to be evidence for the existence of a strong and statistically significant degree of positive *spatial dependence*[4] in the distribution of regional effects. Their analysis shows a

[4]Spatial dependence as a term refers to the spatial relationship of variable values. The presence of a spatial

strong geographic pattern. In particular, spatial heterogeneity presents oneself in the form of two spatial clusters of rich and poor regions. (Márguez et al., 2011.)

In Table 1 I have collected some characteristics from previous VAR studies. Span of time series is typically around thirty to forty years. In most studies annual data has been used since capital stock estimates are rarely available as a quarterly series. Depending on the scope of the study both structural and non-structural approaches to modeling have been used. Previous studies also show different approaches to the issue of non-stationarity. Some studies have settled the issue by using first difference series, while others use vector error correction models in order to maintain the original variable dynamics.

Author	Country	Period	Model	Output effect
Crowder and Himarios (1997)	US	1947–1989	VAR(VECM)	+
Batina (1998)	US	1948–1993	VAR(VECM)	-
Pereira (2000)	US	1956–1997	VAR(FD)	+
Pereira and Roca-Sagales (2001)	Spain	1970–1993	VAR(FD)	+
Kamps (2005)	OECD	1960–2001	VAR(VECM)	+/-
Marquez et al. (2011)	Spain	1972–2000	VAR(SVAR)	+/-

Table 1: Characteristics from previous VAR studies.

2.2 Studies on Transport Infrastructure and Spillover Effects

Many studies have recorded lower elasticities for infrastructures when carried out on a sub-national scale. This indicates that the infrastructures of a region have effects not only on that particular region, but as well as on other regions connected by a network of transport infrastructures. In other words, transport infrastructures might generate positive or negative external effects beyond the regions where they are located. Studies quantifying these external effects (or the regional spillovers) are, however, scarce in number. Cantos et al. (2005) point out that lack of attention to the possible existence of regional spillovers might be due to the fact that it is difficult to find countries that are divided in regions with substantial political power. Furthermore, public capital data at the regional level is rarely available. In literature, empirical evidence from Spain and the USA are overly represented since they fit into these conditions.

Most empirical results are based on the estimation of aggregated production functions (Boarnet, 1998; Holtz-Eakin & Schwartz, 1995; Cantos et al., 2005). As mentioned earlier, Boarnet's (1998) results indicated significant negative spillovers for street and highway capital in county

dependence necessitates the modeling of the joint dynamics, which in time series context requires introducing, next to temporal lags, the concept of spatial lags. (Dewachter et al. 2012.)

level in California. Holtz-Eakin and Schwartz (1995) instead found no evidence of quantitatively important productivity spillovers when testing it for state highway investments.

Pereira and Roca-Sagalés (2003) estimated region-specific VAR models in order to capture the spillover effects of public capital formation. Their approach includes both public capital spend within the region itself and, additionally, public capital spend outside the region. Thus they estimated both the marginal product for each region for the public capital spent in the region itself and the marginal product for each region for the public capital located elsewhere. Pereira and Roca-Sagalés (2003) draw a conclusion that for some of the regions, six out of seventeen, the direct effects of public capital installed in the region are more relevant than the spillover effects from public capital installed outside the region. For the remaining regions the spillover effects were shown to be relatively more important than the direct effects of public capital installed in the region. All these regions can also be described as 'peripherial' regions, indicating a clear geographical pattern in the importance of regional spillovers. (Pereira & Roca-Sagalés, 2003.)

Also Moreno and López-Bazo (2007) argue that the inconclusive nature of the literature on the regional effects of infrastructure is, most likely, partly because of the fact that it ignores spillover effects. They pay special attention to the spatial dimension of the impact of the public capital. Compared to many other studies, they make two important assumptions. First, they assume that the effect of infrastructure on productivity depends on the type of public infrastructure under consideration. They divide infrastructure into (1) *local infrastructure* that may be thought of as enhancing economic activity in the area where it is located, and (2) *transport and communication infrastructure* that may produce both positive and negative benefits in the area where they are located and, moreover, spillovers to other regions. Second, they assume that spillovers can be either positive or negative[5] and check in the analysis part which of these two hypotheses on the spillover effect of infrastructures is in fact valid.

According to Moreno and López-Bazo (2007), it seems that both public capital components, local and transportation, enhance regional productivity since the external economies they generate obtain a slight increases in returns. Testing spillover effects yields, however, different conclusions for the two components. Local public capital seems to have non-significant spillover impact. This result implies that domestic public capital benefits productivity in the region where it is introduced, without neither positive nor negative significant effect on nearby regions. In contrary, transport infrastructure capital in neighboring regions seems to have a

[5]If a positive spillover existed, it can be interpreted in a way that the closer the two regions, the stronger the interaction between them. On the other hand, a negative spillover would be stronger across regions that are close substitutes as locations for production. (Moreno & López-Bazo, 2007.)

significant negative effect. The authors also argue that "the negative spillover arising from factor migration from regions with poor transport infrastructure endowment to regions with good endowments counteracts the positive spillover caused by the connectivity characteristic of most transport public capital". Moreover, Moreno and López-Bazo (2007) obtain a conclusion that the (initial) level of public capital stock affects the results. Returns to both local and transport capital decreased with improvements in endowment for an average province in Spain during the period under analysis.

Bronzini et al. (2009) examined the role of R&D, human capital and public infrastructure as determinants of long-run regional productivity with geographical spillovers in Italy. They found that there exists a long-run equilibrium between the productivity level and all three kinds of examined capital (human capital with the strongest impact on productivity). Bronzini et al. (2009) argue that the contribution of these factors should be examined within a unified framework if they all affect productivity and interact with each other.

Clearly the empirical relevance of regional spillovers of public capital remains as an unresolved issue. At least in the case of US where majority of studies are focused on. In the case of Spain the results are more in line, pointing out that spillover effects are indeed significant and explain partly why aggregated (national level) estimates tend to be higher than disaggregated (sub-national level) estimates.

3 Data

This section describes how the data used in empirical analysis is constructed. Though I would prefer to use as recent data as possible, considering the aim of this thesis, the comparability as well as the level of disaggregation of time series are the key issues instead. Especially disaggregation of public capital stock into transport infrastructure-related and non-related fixed public capital at regional level is a critical requirement. Moreover, analysing the long-run dynamic effects requires long enough time series of the variables used and time horizon is often more important than the frequency of data. As Juselius (2006) points out, in general for macroeconomic variables it is difficult to obtain reasonably long, high-quality aggregated time series since new components can enter, or usually enter, the aggregates and new regulations change the behaviour.

3.1 Finnish Regions and Data Description

Finland is composed of 20 regions[6]. For each region apart from Ahvenanmaa, four key variables for the period 1975-2004 are introduced: (1) the real gross domestic output produced (Y), (2) employment in number of workers (E), (3) the net private non-residential capital stock (P), and (4) the net transport infrastructure capital stock (G). The variables were chosen based on the choice of variables in related literature. This enables the comparison and contrasting the findings to existing empirical literature. The regional series for Y as well as for E are taken from Statistics Finland regional accounting databases (OSF 2016). The regional transport infrastructure stock comprises capital owned by local and national administrations (S1311, S1313 in sectoral classification), including all transport modes (roads, ports, airports, railways). Private capital series (P) excludes the residential capital which forms approximately half of the total private capital stock. All the series are in year 2000 prices. Figure 1 illustrates the national level time series for above mentioned variables both in levels and first differences. For the analysis all variables are expressed in natural logarithms[7] and from now on, I denote the transformed variables by lower-case letters. Thus the vector of endogenous variables can be presented as $X_t \equiv \left[\begin{array}{cccc} g_t, & p_t, & e_t, & y_t \end{array} \right]'$.

[6] I use the regional classification of Statistics Finland from year 2008 (Regions 2008) that includes Itä-Uusimaa as an independent region.

[7] The choice of using log variables is done mostly for the convenience in interpreting the results, as changes in variables can be taken as percentages.

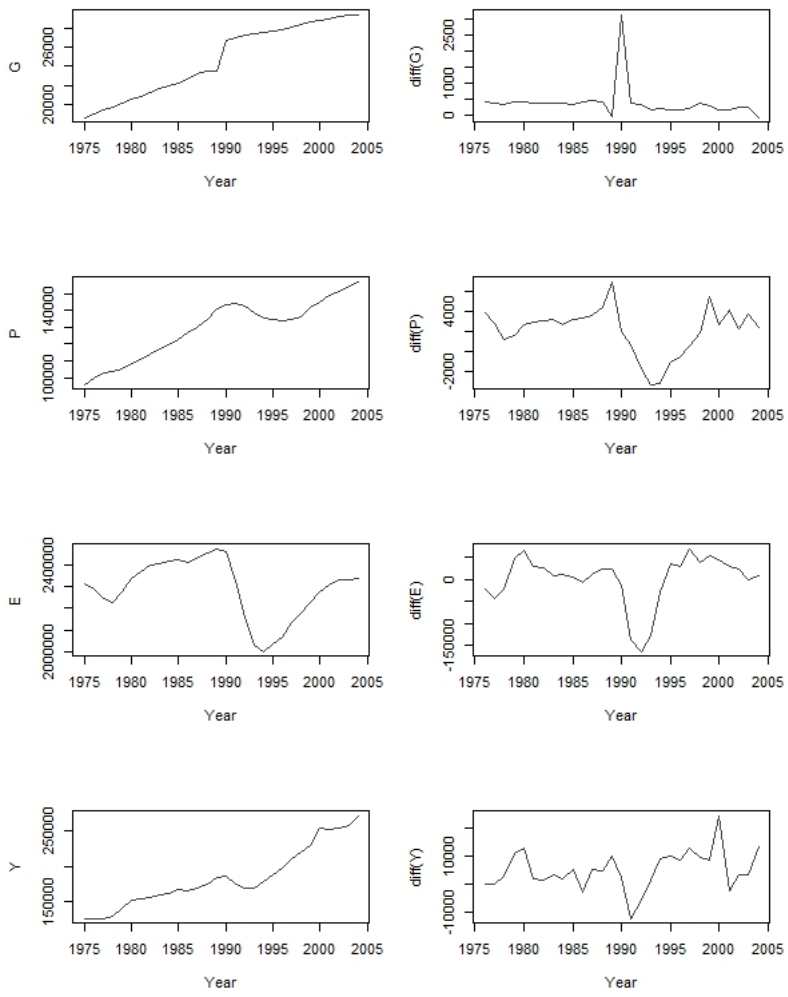

Figure 1: Level series of variables G, P, E, and Y (on the left) and their first differences (on the right).

Few things are noteworthy from Figure 1. First of all, in the level series of aggregated transport infrastructure capital stock it is easy to spot a shift around year 1990. Other series do not exhibit same kind of behaviour but rather the opposite, bearing in mind that year 1990 marks as a starting year of period of severe recession in Finland. The regional level series show that there are substantial differences in the evolution of capital stock estimates. Interestingly, for many regions the fixed priced transport infrastructure capital stock series are declining. This means that depreciations have been exceeding gross investments for those regions year after year. However, since the aggregated stock of G is upward sloping, as can be seen from Figure 1, the increase in transport infrastructure capital on some regions outweighs this negative

development on other regions.

3.2 Methodology of Effective Capital Stock Estimation

When one argues that output in one region can be affected by public capital investments in close-by regions, it also translates to the concept of public capital stock. The effective stock of public capital in region i (G_i^e) must then differ from the within-region stock (G_i) , due to the contribution of the stock of other regions. That is why, following Holtz-Eakin and Schwartz (1995), the relevant stock of capital for explaining variations in the region's aggregate production should include some kind of measure of public capital in other regions. Following Holtz-Eakin and Schwartz (1995), I define G_i^e as:

$$G_i^e = G_i + \prod_j^N G_j^{\theta w_{ij}}, \tag{3.1}$$

where j denotes nearby regions ($j \neq i$) and w_{ij} the weight of other regions' public capital stock. Spatial heterogeneity is taken into account through w_{ij}. Parameter θ measures the effect of the public capital of other regions on the effective capital. One can easily see that when $\theta = 0$, the effective and actual measures of public capital stock are equal. On the other hand significantly nonzero θ can be viewed as a test of the spillover effect.

How to measure the intensity of relations between regions (or w_{ij} in 3.1) as objectively as possible remains as the most critical question in spillover related studies. The most popular way has been to use the geographical proximity between regions. In the simplest form that means weighting neighbouring or adjacent regions equal to one and non-bordering regions equal to zero. Alternatively, some authors have used an approach where the weights are defined in terms of the inverse of the distance from other regions (e.g. Álvarez-Ayuso et al., 2014). However, it is also possible to measure commercial relations between regions with trade flows between them. The usefulness of trade flows can be justified especially in the context of transport infrastructure, as the trade flows between regions measure - besides the value of the trade between regions - the fact that a greater amount of goods sold implies a greater amount of goods transported, and therefore also greater use of infrastructures between regions.

The aggregate methods to measure spillovers have received criticism during recent years, mainly due to the lack of attention to commercial relations between regions (see for example Álvarez-Ayuso et al., 2014 or Cantos et al., 2005). Álvarez-Ayuso et al. (2014) introduced a new way of measuring transport infrastructure capital stock. Instead of pure monetary value of the capital stock they aim to measure the real benefit obtained by a region when accessing

markets. This is done by weighting the infrastructure stock with trade data. The approach allows to perform an analysis of the effects on production of the internally used transport infrastructure (direct effect). Naturally the part of the infrastructure stock that is not used by a region internally is exported to other regions to import their goods (exported stock). Álvarez-Ayuso et al. (2014) calculate the internal and exported infrastructure stocks by performing network analysis in a Geographical Information System (GIS). This approach allows the public capital stock actually used in trading activities to be accounted for. Based on the assumption of generalized transportation costs they calculate the values of 'used public capital stock' (combining the internal and imported stock) for each region and use these new stock variables when they analyse the role of transport infrastructure on regional gross domestic product.

Next I will shortly present how the 'effective' transport infrastructure capital stocks for Finnish regions used in this thesis are constructed. The two main components used are the net transport infrastructure capital stocks for regions ($G_i^{in}, i = 1, \ldots, N$), and a weight matrix $\mathbf{W}$ based on trade flows between regions. Naturally sum of the within-region transport infrastructure stocks equals the national level variable, that is $G = \sum_{i=1}^{N} G_i^{in}$. The $(N \times N)$-dimensional matrix $\mathbf{W}$ consists of region specific weights w_{ij}. Elements satisfy $w_{ii} = 0$ and $\sum_{j=1}^{N} w_{ij} = 1$ (the rows sum up to one). The matrix aims to reflect the network of relationships in the regional system. Since elements on diagonal get values zero, multiplying a vector $\mathbf{G}^{in} \equiv \left[G_1^{in}, \ldots, G_N^{in}\right]$ by the weight matrix $\mathbf{W}$ produces some sort of estimate for the transport infrastructure capital stocks that regions utilize to import and export goods. I denote this vector as $\mathbf{G}^{out} = \mathbf{W} \times \mathbf{G}^{in}$. The effective capital stock is then simply sum of the net transport infrastructure capital stock located within the region itself and the estimated stock of transport infrastructure outside the region, so that $\mathbf{G}^{eff} = \mathbf{G}^{in} + \mathbf{G}^{out}$.

3.3 Regional Analysis of the Evolution of Variables

The regional distribution of all variables, in percentage points, is presented in Table 2. The distribution is based on averages from entire sample period (from 1975 to 2004). One region, Uusimaa, is responsible for almost one-third of the total production. In addition its share in terms of employment is notably lower which reflects an above-average productivity level. Moreover, together with the regions of Varsinais-Suomi and Pirkanmaa, these three regions account for almost half of the total production in Finland. The aggregate results will be largely affected by estimates obtained for these regions.

In the context of this research, the ratio of GDP over transport infrastructure capital stock is one way to measure which regions are oversupplied and undersupplied in terms of transport infrastructure capital stock in Finland (see eg. Roca-Sagalés and Sala (2010) for similar method with Spanish data). I have calculated this ratio both for capital stock located in the region itself as well as for the effective transport infrastructure capital stock (calculated as explained in previous section). The regions are ranked based on GDP to capital stock ratio in columns seven and eight in Table 2. The rankings as well as the actual ratio values vary a lot between GDP to regional capital stock and to effective capital stock ratios. This is mostly corollary from the fact the region of Uusimaa is the most important interregional trading partner for every other region in Finland. Considering that the net public transport capital stock is highest in Uusimaa, and keeping in mind the methodology for calculating the effective capital stocks, the result is not surprising.

I will not subdivide regions into groups based on endowment of transport infrastructure capital stock as Roca-Sagalés and Sala (2010) have done. It should be, however, interesting to see if regions with low rank produce different kind of results for long-run elasticities compared to regions with higher rank. Moreover, the relative amount of transport infrastructure capital within region can be measured as percentage of total public capital stock. This is presented in Figure 2. It appears that for five regions, namely Pohjois-Karjala, Kanta-Häme, Kymenlaakso, Uusimaa and Etelä-Savo - ordered from highest to lowest - the transport infrastructure capital stock forms at least half of the total public capital stock. On the other end are regions like Keski-Suomi and Pohjois-Savo, for which the corresponding share is roughly 20 %.

Region	Y	E	P	G	G^{eff}	rank(Y/G)	rank(Y/G^{eff})
Uusimaa	29.7	27.5	26.3	36.0	11.1	5	19
Varsinais-Suomi	9.0	8.7	8.2	3.7	5.3	18	18
Satakunta	5.1	4.8	5.4	2.2	5.1	16	14
Kanta-Häme	3.0	3.2	2.8	9.8	7.7	2	4
Pirkanmaa	8.0	8.4	7.2	4.6	6.7	10	16
Päijät-Häme	3.3	3.8	3.3	1.4	4.8	17	8
Kymenlaakso	4.2	3.8	5.0	7.5	6.1	4	7
Etelä-Karjala	3.0	2.6	4.0	1.5	3.8	14	10
Etelä-Savo	2.3	3.1	2.5	4.3	5.4	3	5
Pohjois-Savo	4.0	4.6	4.3	2.3	4.1	11	13
Pohjois-Karjala	2.5	3.1	2.8	11.1	6.6	1	2
Keski-Suomi	4.4	4.7	4.6	2.2	4.1	13	15
Etelä-Pohjanmaa	3.0	3.8	2.8	1.8	4.8	9	6
Pohjanmaa	3.5	3.5	3.8	1.9	4.3	12	11
Keski-Pohjanmaa	1.2	1.3	1.2	0.6	3.3	15	3
Pohjois-Pohjanmaa	6.1	6.2	6.5	4.7	5.1	7	17
Kainuu	1.4	1.8	1.6	1.4	3.9	6	1
Lappi	3.4	3.6	4.6	2.2	3.9	8	12
Itä-Uusimaa	2.9	1.5	2.9	0.6	3.9	19	9

Table 2: Regional distribution of GDP, employment, and private and transport infrastructure capital stock, and ranking orders of output over transport infrastructure ratios, 1975-2004.

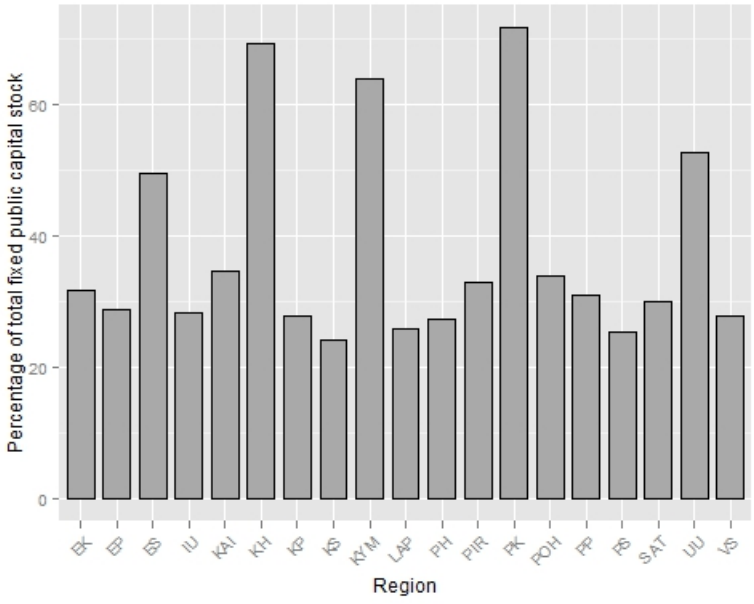

Figure 2: Percentage of transport infrastructure capital stock of total public capital stock, regions in alphabetical order. Source: Own calculations.

4 Methodology

4.1 Some Background and the Issue of Non-stationarity

Under the assumption that the relation between output and transport infrastructure capital stock can be empirically identified, the statistical estimation problem has to be addressed. This section covers the econometric methodology underlying the empirical application in Section 5.

Typically VAR models are used for three purposes: (1) assessing the causal effects of the endogenous variables on each other, (2) investigating the dynamic impact of changes in one variable on the others in the model, and (3) exploring the amount of the variance in each variable that can be attributed to changes in each variable itself and the other variables in the system of equations.

First one is usually achieved by testing a hypothesis whether one variable is statistically useful for predicting another. This is based on an idea called *Granger causality*. It is said that variable i Granger causes variable j, if past values of i (in addition to past values of variable itself) help to predict future values of j.

Assessing the dynamic impacts is generally done by impulse response analysis (IRA). Impulse responses are found by inverting the system of VAR equations to find the moving average (MA) representation of the model (subject to identification assumptions). MA representation is necessary if the aim is to look at the impact of exogenous shocks to the equations in the system and trace out the response of the system to this particular shock.

The third traditional way of assessing a VAR model is known as the forecast error variance decomposition (FEVD). With FEVD method it is possible to examine how much of the forecast error in the variables is due to variable i and how much can be attributed to variable j. This of course helps us to explain how innovations or changes in one variable lead to change in another. Intuitively, the more of a variable's forecast errors are attributed to another variable, the more important that second variable is in explaining the first variable.

Multivariate time series analysis naturally differs from univariate time series analysis. The multivariate nature of the data complicates things quite a bit and negates the use of some diagnostic tools such as autocorrelation functions for specification searching. Moreover, in order to estimate the reduced-form[8] VAR model one has to specify the lag length p. Also it is necessary to identify the contemporaneous relationships among the variables in the model if

[8]Impression 'reduced-form' is often used for VAR model since the variation in vector of k variables, $\mathbf{x}_t$, is described as a function of lagged values of the process (Juselius, 2006).

one wants to interpret the dynamics by looking at shocks to the equations. Most importantly, not just any method of the estimation can be used for the VAR model since (non)stationarity of the variables and the number of cointegration relations among them determines the accurate method.

Non-stationarity is an issue that often causes problems when applying statistical and econometric methods. Many macroeconomic variables exhibit non-stationary behaviour, by which it is meant that the variables have no tendency to return to a constant mean or a linear trend. Instead, the variables 'wander' around, which more accurately put means that the variables seem to be unit root processes and characterized by stochastic trends. Output is usually recognised as a non-stationary variable since the present level of output greatly depends on ongoing technological innovations and acquired knowledge. Also private and public capital stocks and employment are variables that are likely to exhibit non-stationary behaviour. (Eriksson, 2005; Kamps, 2005)

It is important to take into account the problem of non-stationarity if the goal is to even try to make correct evaluations and draw some statistical and economic conclusions from empirical models. Many standard estimation methods are based on the assumption that time series are stationary. Most famous example about misleading statistical inference is perhaps a linear regression involving non-stationary variables. This kind of setting may give spurious results that have no meaningful interpretations. (Eriksson, 2005)

One possible solution to the problem of non-stationarity is to transform the series into first differences. However, this is often not a feasible approach if one wants to estimate economic relations and test hypotheses derived from economic theory. Relations formulated in differences correspond to short-run behaviour, whereas economic theory *de facto* concerns relationships among variables that hold in the long-run. Introducing the concept of cointegration has been a major contribution to the analysis of relationships among non-stationary variables. A set of non-stationary variables that share some stochastic trends can still have a non-spurious relationship among them in the presence of cointegration.

4.2 The Vector Autoregressive Process

Instead of a single time series process, the scope of this thesis is on situation where a vector of k variables is observed. The number of variables is four ($k = 4$) in the empirical part of this thesis. From now on, x_t will be used to denote both a random variable and its realization.

Starting point is the $k \times 1$ dimensional vector $\mathbf{x_t}$:

$$\mathbf{x}_t = \begin{bmatrix} x_{1,t} \\ x_{2,t} \\ \vdots \\ x_{k,t} \end{bmatrix}, \; t = 1, \ldots, T.$$

A p-th order vector autoregressive process, denoted VAR(p), can be written as:

$$\mathbf{x}_t = \mathbf{A}_1 \mathbf{x}_{t-1} + \mathbf{A}_2 \mathbf{x}_{t-2} + \cdots + \mathbf{A}_{t-p} \mathbf{x}_{t-p} + \mathbf{\Phi} \boldsymbol{D}_t + \boldsymbol{\varepsilon}_t, \tag{4.1}$$

where $\mathbf{x}_t \equiv [x_{1t}, \ldots, x_{kt}]^{'}$ is a set of variables collected in a $(k \times 1)$ vector as defined above, $\mathbf{A}_1, \mathbf{A}_2, \ldots, \mathbf{A}_p$ are $(k \times k)$ coefficient matrices and $\mathbf{\Phi}$ denotes a $(k \times d)$ matrix of coefficients on deterministic terms (such as a constant, seasonal dummies and intervention dummies, or other regressors that we consider fixed and non-stochastic) collected in the $(d \times 1)$ vector $\mathbf{D}_t$. Moreover, $\boldsymbol{\varepsilon}_t = [\varepsilon_{1t}, \ldots, \varepsilon_{kt}]^{'}$ is a $k-$dimensional white noise process with mean zero, $E[\boldsymbol{\varepsilon}_t] = \mathbf{0}$, and a $(k \times k)$ symmetric positive definite covariance matrix $E\left[\boldsymbol{\varepsilon}_t \boldsymbol{\varepsilon}_t^{'}\right] = \mathbf{\Sigma}_\varepsilon$.

The model can also be written with a lag operator notation:

$$\mathbf{A}(L)\, \mathbf{x}_t = \mathbf{\Phi} \boldsymbol{D}_t + \boldsymbol{\varepsilon}_t, \tag{4.2}$$

where $\mathbf{A}(L) = \mathbf{I}_K - \mathbf{A}_1 L - \mathbf{A}_2 L^2 - \cdots - \mathbf{A}_p L^p$. The process is classified as stable if

$$det\left(\mathbf{I}_K - \mathbf{A}_1 z - \mathbf{A}_2 z^2 - \cdots - \mathbf{A}_p z^p\right) \neq 0 \text{ for } |z| \leq 1,$$

so that the polynomial defined by the determinant of the autoregressive operator has no roots in and on the complex unit circle. This is also called the *root condition*. In addition, if it is assumed that the process has been initiated in the infinite past, the process generates stationary time series. Stationary (or weakly stationary, to be precise) time series have time-invariant means, variances and covariance structure.

When the process is stationary, presentation in (4.2) can be inverted into moving average (MA) presentation so that $\mathbf{x}_t$, $t = 1, \ldots, T$, is expressed as a function of past and present

shocks, $\boldsymbol{\varepsilon}_{t-j}$, $j = 0, 1, \ldots$, initial values $\mathbf{x}^0$, and deterministic components $\boldsymbol{D}_t$ (Juselius, 2006):

$$\begin{aligned}
\mathbf{x}_t &= \mathbf{A}^{-1}(L)(\boldsymbol{\Phi}\boldsymbol{D}_t + \boldsymbol{\varepsilon}_t) + \tilde{\mathbf{x}}^0,\ t = 1, \ldots, T \\
&= |\mathbf{A}(L)|^{-1}\mathbf{A}^{\alpha}(L)(\boldsymbol{\Phi}\boldsymbol{D}_t + \boldsymbol{\varepsilon}_t) + \tilde{\mathbf{x}}^0,\ t = 1, \ldots, T \\
&= \left(\mathbf{I} + \mathbf{C}_1 L + \mathbf{C}_2 L^2 + \cdots\right)(\boldsymbol{\Phi}\boldsymbol{D}_t + \boldsymbol{\varepsilon}_t) + \tilde{\mathbf{x}}^0,\ t = 1, \ldots, T
\end{aligned}$$

where $\tilde{\mathbf{x}}^0$ includes the effect of the initial values of the process and its dynamics. For $\mathbf{C}_j = f(\mathbf{A}_1, \ldots, \mathbf{A}_p)$ a recursive formula can be given if the VAR process is stationary (see Johansen, 1995).

When the VAR process is non-stationary, $\mathbf{A}(L)$ is non-invertible and the $\mathbf{C}_j = f(\mathbf{A}_1, \ldots, \mathbf{A}_p)$ matrices have to be derived under the assumption of reduced rank. This case is discussed later in more detail.

4.3 The Unrestricted VAR Model

The unrestricted VAR model with Gaussian errors and deterministic terms $\boldsymbol{D}_t$ is defined by

$$\mathbf{x}_t = \mathbf{A}_1\mathbf{x}_{t-1} + \mathbf{A}_2\mathbf{x}_{t-2} + \cdots + \mathbf{A}_{t-p}\mathbf{x}_{t-p} + \boldsymbol{\Phi}\boldsymbol{D}_t + \boldsymbol{\varepsilon}_t,\ t = 1, \ldots, T, \tag{4.3}$$

where the errors $\boldsymbol{\varepsilon}_t$ are independent Gaussian with mean zero and covariance matrix $\boldsymbol{\Omega}$, $\boldsymbol{\varepsilon}_t \sim in(\mathbf{0}, \boldsymbol{\Omega})$. The initial values $\mathbf{x}_{-p+1}, \mathbf{x}_{-p+2}, \ldots, \mathbf{x}_0$ are fixed and the unrestricted parameters are then

$$(\mathbf{A}_1, \ldots, \mathbf{A}_p, \boldsymbol{\Phi}, \boldsymbol{\Omega}).$$

Using the notation $\mathbf{Z}' = \left[\mathbf{x}'_{t-1}, \ldots, \mathbf{x}'_{t-p}, \boldsymbol{D}'_t\right]$ for the stacked vector and $\mathbf{A}' = [\mathbf{A}_1, \ldots, \mathbf{A}_p, \boldsymbol{\Phi}]$ for the corresponding parameters, the model expressed in these variables becomes

$$\mathbf{x}_t = \mathbf{A}'\mathbf{Z}_t + \boldsymbol{\varepsilon}_t,\ t = 1, \ldots, T. \tag{4.4}$$

The ordinary least squares (OLS) estimator of $\mathbf{A}$ is (see more detailed derivation in Lütkepohl, 2005),

$$\hat{\mathbf{A}} = \left[\hat{\mathbf{A}}_1 : \cdots : \hat{\mathbf{A}}_p\right] = \mathbf{x}_t\mathbf{Z}'_t\left(\mathbf{Z}_t\mathbf{Z}'_t\right)^{-1}, \tag{4.5}$$

which under standard assumptions (see e.g. Lütkepohl, 2005) is consistent and asymptotically

normally distributed. The asymptotic properties are then summarized as,

$$\sqrt{T}\text{vec}\Big(\hat{\mathbf{A}}-\mathbf{A}\Big)\xrightarrow{d}N\left(\mathbf{0},\Sigma_{\hat{A}}\right). \tag{4.6}$$

Also the covariance matrix $\mathbf{\Omega}$ can be estimated in the usual way, that is, by using the OLS residuals. The residuals are now written as $\hat{\boldsymbol{\varepsilon}}_t=\mathbf{x}_t-\hat{\mathbf{A}}\mathbf{Z}_t$ and the estimator as

$$\hat{\mathbf{\Omega}}=\frac{1}{T}\sum_{t=1}^{T}\hat{\boldsymbol{\varepsilon}}_t\hat{\boldsymbol{\varepsilon}}_t^{'}. \tag{4.7}$$

The estimator in (4.7) is consistent and asymptotically normally distributed independently of $\hat{\mathbf{A}}$. It can also be said that $\sqrt{T}\left(\hat{\mathbf{\Omega}}-\mathbf{\Omega}\right)$ has an asymptotic normal distribution if sufficient moment properties are imposed.

Since the errors are Gaussian it is also possible to derive the equations for estimating $\mathbf{A}$ and $\mathbf{\Omega}$ by analysing the log likelihood function. This corresponds to finding the expression for $\mathbf{A}$ and $\mathbf{\Omega}$ for which the first-order derivatives of the likelihood function are equal to zero. The log likelihood function is written as

$$\ln L\left(\mathbf{A},\mathbf{\Omega}\right)=-\frac{1}{2}T\ln(2\pi)-\frac{1}{2}T\ln|\mathbf{\Omega}|-\frac{1}{2}\sum_{t=1}^{T}\left(\mathbf{x}_t-\mathbf{A}^{'}\mathbf{Z}_t\right)^{'}\mathbf{\Omega}^{-1}\left(\mathbf{x}_t-\mathbf{A}^{'}\mathbf{Z}_t\right),$$

from which $\partial\ln L/\partial\mathbf{A}=\mathbf{0}$ may be calculated, which leads to the equations for estimating $\mathbf{A}$,

$$\sum_{t=1}^{T}\mathbf{x}_t\mathbf{Z}_t^{'}=\tilde{\mathbf{A}}^{'}\sum_{t=1}^{T}\mathbf{Z}_t\mathbf{Z}_t^{'}$$

and the usual regression estimator,

$$\tilde{\mathbf{A}}=\left(\sum_{t=1}^{T}\mathbf{Z}_t\mathbf{Z}_t^{'}\right)^{-1}\left(\sum_{t=1}^{T}\mathbf{Z}_t\mathbf{x}_t^{'}\right)=\mathbf{M}_{zz}^{-1}\mathbf{M}_{zx}. \tag{4.8}$$

Moreover, when $\partial\ln L/\partial\mathbf{\Omega}=\mathbf{0}$ is solved, the result is an estimator of $\mathbf{\Omega}$:

$$\tilde{\mathbf{\Omega}}=T^{-1}\sum_{t=1}^{T}\left(\mathbf{x}_t-\tilde{\mathbf{A}}^{'}\mathbf{Z}_t\right)\left(\mathbf{x}_t-\tilde{\mathbf{A}}^{'}\mathbf{Z}_t\right)^{'}=T^{-1}\sum_{t=1}^{T}\hat{\boldsymbol{\varepsilon}}_t\hat{\boldsymbol{\varepsilon}}_t^{'}=\mathbf{M}_{xx.z}=\mathbf{M}_{xx}-\mathbf{M}_{xz}\mathbf{M}_{zz}^{-1}\mathbf{M}_{zx}. \tag{4.9}$$

Above I use the notation $\mathbf{M}_{zx}=T^{-1}\sum_{t=1}^{T}\mathbf{Z}_t\mathbf{x}_t^{'}$ for any two processes $\mathbf{x}_t$ and $\mathbf{Z}_t$.

Now it can be noted that ML estimators (4.8) and (4.9) correspond to 'usual' OLS estimators. Furthermore, the maximal value of the log likelihood function for $\tilde{\mathbf{A}}$ and $\tilde{\mathbf{\Omega}}$ can be found from:

$$\ln L_{max} = \frac{1}{2}T\ln(2\pi) - \frac{1}{2}T\ln|\tilde{\mathbf{\Omega}}| - \frac{1}{2}\sum_{t=1}^{T}\left(\mathbf{x}_t - \tilde{\mathbf{A}}'\mathbf{Z}_t\right)'\tilde{\mathbf{\Omega}}^{-1}\left(\mathbf{x}_t - \tilde{\mathbf{A}}'\mathbf{Z}_t\right).$$

It can be shown that $\ln L_{max} = -\frac{1}{2}T\ln|\tilde{\mathbf{\Omega}}|+$ constant terms, i.e. apart from constant terms, the maximum of the log likelihood function is proportional to the log determinant of the residual covariance matrix $\tilde{\mathbf{\Omega}}$. This result is useful for deriving many of the test procedures as well as in the derivation of the maximum likelihood estimator for the cointegrated VAR model. (Juselius, 2006.)

The asymptotic equivalence of OLS and ML estimators of $\mathbf{A}$ and $\mathbf{\Omega}$ can be shown with moderate effort (Lütkepohl, 2005). Thus, if $\mathbf{x}_t$ is stationary and stable Gaussian VAR(p) process, $\tilde{\mathbf{A}}$ and $\tilde{\mathbf{\Omega}}$ are consistent estimators and $\sqrt{T}\left(\tilde{\mathbf{A}} - \mathbf{A}\right)$ and $\sqrt{T}\left(\tilde{\mathbf{\Omega}} - \mathbf{\Omega}\right)$ are asymptotically normally distributed.

The above calculations show that for the unrestricted VAR model, basing estimation on the sample $\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_T$, the k equations of the VAR can be estimated separately by OLS. Sims, Stock and Watson (1990) have shown that this result holds also in the case in which some variables are integrated and possibly cointegrated. However, as Kamps (2005) reminds, other quantities derived from these estimates may not be consistent. Phillips (1998) shows in more detail how impulse response functions (IRFs) and forecast error variance decompositions (FEVDs) are inconsistent at long horizons in unrestricted VARs with some unit roots. In contrast, Phillips (1998) proposes that reduced rank regressions produce IRFs and FEVD estimates that are consistent and predictions that are asymptotically optimal when the cointegration rank is correctly specified or consistently estimated. Since in this thesis the interest lies especially in impulse response analysis, it is important to carefully investigate the cointegration properties of the VAR system.

4.4 The Cointegration Model

Trending means and changing variances are quite common for macroeconomic variables. Also the variables used in this thesis are likely to exhibit non-stationary behaviour, as can be seen from Figure 1. Consequently, if one wants to analyse the original variables or their logarithms instead of the rate of change, it is crucial to introduce models that account for the non-stationary features of the data. In this section I define in more detail what we mean

by *integrated* and *cointegrated* processes. Moreover, a vector error correction model (VECM), a model that offers a convenient way to parameterize common trends between variables, is presented in this section.

4.4.1 Integrated Processes

At this point it has already been stated that the stability of a VAR(p) process (4.1) is defined by the so-called root condition. In other words, the polynomial defined by

$$det\left(I_K - \mathbf{A}_1 z - \cdots \mathbf{A}_p z^p\right)$$

has no roots in and on the complex unit circle (Lütkepohl, 2005). When considering a univariate AR(1) process, $y_t = \alpha y_{t-1} + u_t$, if α is equal to one, the process is called a *random walk*. By substitution it is easy to see that random walk consists of the sum of all disturbances of the previous periods, starting at $t = 0$ with some fixed y_0:

$$y_t = y_{t-1} + u_t = y_{t-2} + u_{t-1} + u_t = \cdots = y_0 + \sum_{i=1}^{t} u_i.$$

The expected value or the first moment of a random walk process y_t is defined as (assuming u_t is white noise with variance σ_u^2) :

$$E\left(y_t\right) = E\left(y_0 + \sum_{i=1}^{t} u_i\right) = y_0.$$

The process y_t clearly does not have time invariant second moment, since

$$Var\left(y_t\right) = Var\left(\sum_{i=1}^{t} u_i\right) = tVar\left(u_t\right) = t\sigma_u^2.$$

If $t \to \infty$, the variance of a random walk tends to infinity. The correlation of the process can also be shown to tend towards one for any integer h:

$$\begin{aligned} \text{Corr}\left(y_t, y_{t+h}\right) &= \frac{E\left[\left(\sum_{i=1}^{t} u_i\right)\left(\sum_{i=1}^{t+h} u_i\right)\right]}{\left[t\sigma_u^2\left(t+h\right)\sigma_u^2\right]^{1/2}} \\ &= \frac{t}{\left(t^2+th\right)^{1/2}} \to 1 \end{aligned}$$

if $t \to \infty$. This means that y_t and y_s are strongly correlated even when h gets high values.

Random walk with a drift is the same process as above but with a nonzero constant term ν, $y_t = \nu + y_{t-1} + u_t$. This process has a deterministic linear trend in the mean, which can be shown by writing y_t with repetitive substitution as

$$y_t = y_0 + t\nu + \sum_{i=1}^{t} u_i$$

and, consequently, $E(y_t) = E\left(y_0 + t\nu + \sum_{i=1}^{t} u_i\right) \overset{lin.}{=} y_0 + t\nu$.

As Lütkepohl (2005) notes, also higher order AR processes can poses a behaviour similar to that of a random walk. For AR(p) process such as

$$y_t = \nu + \alpha_1 y_{t-1} + \alpha_2 y_{t-2} + \cdots + \alpha_p y_{t-p} + u_t,$$

it is possible that one $\alpha_1 z - \cdots \alpha_p z^p$ has a root for $z = 1$. Furthermore, $1 - \alpha_1 z - \cdots - \alpha_p z^p = (1 - \lambda_1 z) \cdots (1 - \lambda_p z)$, where $\lambda_1, \ldots, \lambda_p$ are the reciprocals of the roots of the polynomial. If only one unit root exists in the AR(p) process, and assuming that all other roots are outside the complex unit circle, the behaviour is same as in the univariate (random walk) case. That is, the variance of the process is linearly increasing, the process has a linear trend in mean (if $\nu \neq 0$) and the correlation tends to one. If the process has exactly one unit root, it is called a $I(1)$ process that can be made stable (as well as possibly stationary) by taking first differences of the original process.

The number of roots on the unit circle is of course not restricted to one, though in empirical part I show that all variables used in this thesis are integrated of order one. A univariate process integrated of order higher than one, a $I(d)$ process, can be made stable by differencing d times. More formally, $\triangle^d y_t = (1 - L)^d y_t$ is stable and with chosen initial values also stationary. Johansen (1995) has defined the order of integration for the variables in a k -dimensional process $\mathbf{x}_t$ followingly:

Definition 1 $\mathbf{x}_t$ is integrated of order d if $\mathbf{x}_t$ has the presentation $(1 - L)^d \mathbf{x}_t = \mathbf{C}(L)\boldsymbol{\varepsilon}_t$, where $\mathbf{C}(1) \neq \mathbf{0}$, and $\boldsymbol{\varepsilon}_t \sim in(\mathbf{0}, \boldsymbol{\Omega})$.

It seems natural to ask if differencing each $I(d)$ component of a VAR(p) process could solve the problem of stochastic trends. Then VAR analysis with model explained in Ch 4.3 could be performed after differencing the individual variables. Unfortunately differencing may distort the relationship between the original variables. That is the main reason why differencing

approach is not used in this thesis.

4.4.2 Cointegrated Processes and Common Stochastic Trends

Individually integrated variables may be driven by a *common stochastic trend*. If the variables are indeed driven by the same persistent shocks, there must exist a linear combination between them that becomes stationary. These kind of variables are called *cointegrated*. Again I present definition for the order of cointegration in a k -dimensional process $\mathbf{x}_t$ following Johansen (1995):

Definition 2 The $I(d)$ process $\mathbf{x}_t$ is called cointegrated $CI(d,b)$ with cointegrating vector $\boldsymbol{\beta} \neq \mathbf{0}$ if $\boldsymbol{\beta}'\mathbf{x}_t$ is $I(d-b)$, $b = 1, \ldots, d$, $d = 1, \ldots$.

The vector $\boldsymbol{\beta}$ is called a *cointegrating vector*. One should note that this definition of cointegration is significantly more general than the standard notion of Engle and Granger (1987), where all observables are required to have identical integration orders. From Definition 2 one can see that cointegration implies certain linear combinations of the variables of the vector process are integrated of lower order than the process itself. As an example, if all components of $\mathbf{x}_t$ are integrated of order one, $I(1)$, and $\boldsymbol{\beta}'\mathbf{x}_t$ is stationary ($I(0)$), then $\mathbf{x}_t \sim CI(1,1)$. Another interpretation of cointegration is that when two or several variables have common stochastic trends, they will show a tendency to move together in the long-run. The cointegrated relations, $\boldsymbol{\beta}'\mathbf{x}_t$, can then be seen as long-run economic steady-state relations. (Juselius, 2006.)

It is quite obvious that the cointegrating vector is not unique as $a\boldsymbol{\beta}'\mathbf{x}_t$ is also $I(0)$ for any non-zero scalar a. Hence some normalization assumption is required to uniquely identify $\boldsymbol{\beta}$. Also if the $(k \times 1)$ vector $\mathbf{x}_t$ is cointegrated, number of linearly independent cointegrating vectors, r, may be $0 < r < k$. For multiple cointegrating relations it can be said that

$$\mathbf{B}' = \begin{bmatrix} \boldsymbol{\beta}_1' \\ \vdots \\ \boldsymbol{\beta}_r' \end{bmatrix} = \begin{pmatrix} \beta_{11} & \cdots & \beta_{1k} \\ \vdots & \ddots & \vdots \\ \beta_{r1} & \cdots & \beta_{rk} \end{pmatrix}$$

forms a *basis* for the space of cointegrating vectors. Again $\boldsymbol{\beta}_1, \ldots, \boldsymbol{\beta}_r$ are not unique unless some normalization assumptions are made.

For determining r and $\boldsymbol{\beta}$, the procedure introduced by Johansen (1988) can be implemented. The Johansen test method builds on the maximum likelihood approach and allows that more than one cointegration relations may be present. The method is explained more closely in Section 5.

Deterministic terms may as well be present in cointegrated processes and VECMs, and ignoring them completely is out of question. For example, above I have stated that an intercept term in a random walk arouses a linear trend in the mean of the process (compared to that an intercept in a stable AR process implies a constant mean value). Possible deterministic terms include a constant, $\mu_t = \mu_0$, a linear trend term, $\mu_t = \mu_0 + \mu_1 t$, as well as seasonal dummies. It is possible for the linear trend to appear in the variables but not in the cointegration relations, and vice versa (see e.g. Lütkepohl, 2005, for the former case). Deterministic terms affect for example the test statistics and critical values of testing for the rank of cointegration. For example Kamps (2005) has suggested when studying public capital effects with similar variables as in this thesis, that a constant should be included and left unrestricted and the trend should be restricted to the cointegrating space. I will follow this specification in empirical part.

4.4.3 Vector error correction model (VECM)

The unrestricted VAR model presented earlier can be given different parametrizations without changing the value of the likelihood function. The presence of unit roots (i.e. stochastic trends) in the unrestricted VAR model corresponds to non-stationary stochastic behaviour which can be accounted for by a reduced rank ($r < k$) restriction of the long-run levels matrix $\mathbf{\Pi} = \boldsymbol{\alpha}\boldsymbol{\beta}^{'}$, where $\mathbf{\Pi}$ is a $(r \times r)$ matrix and $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ $(r \times k)$ matrices. If the unrestricted VAR model (4.1) is reformulated in terms of differences, lagged differences and levels of the process, the result is the so-called vector error correction model (VECM). In practice this reformulation is done by subtracting $\mathbf{x}_{t-1}$ from both sides and thereafter rearranging the terms. Then standard VECM model for k variables with p lags in the original VAR model and normal errors can be written as:

$$\triangle \mathbf{x}_t = \mathbf{\Pi}\mathbf{x}_{t-1} + \mathbf{\Gamma}_1 \triangle \mathbf{x}_{t-1} + \mathbf{\Gamma}_2 \triangle \mathbf{x}_{t-2} + \cdots + \mathbf{\Gamma}_{p-1} \triangle \mathbf{x}_{t-p+1} + \mathbf{\Phi}\boldsymbol{D}_t + \boldsymbol{\varepsilon}_t, \tag{4.10}$$

where $\mathbf{\Pi} \equiv -\mathbf{I} + \sum_{i=1}^{p} \mathbf{A}_i$ and $\mathbf{\Gamma}_j = -\sum_{i=j+1}^{p} \mathbf{A}_i$, $j = 1, 2, \ldots, p-1$, denote $(k \times k)$ matrices of coefficients, respectively. The error term is assumed to be independently and identically distributed as $in\,(\mathbf{0}, \mathbf{\Omega})$.

Several features make VECM formulation attractive. In VECM all information about long-run effects is summarized in the levels matrix $\mathbf{\Pi}$. That is an important advantage in the context of this thesis. Moreover, the interpretation of the estimates is more intuitive, as the coefficients can be classified into short-run (differences) and long-run (levels) effects. (Juselius, 2006.)

The rank of $\mathbf{\Pi}$ is often referred to as the *cointegrating rank* of the system. The rank $rk\,(\mathbf{\Pi}) = r$

defines the dimensions for matrices $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$. For example in a system of three variables ($k = 3$) with two cointegrating relations ($r = 2$), the first term of RHS in (4.10) can be written as

$$\begin{aligned}\boldsymbol{\Pi}\mathbf{x}_{t-1} &= \boldsymbol{\alpha}\boldsymbol{\beta}^{'}\mathbf{x}_{t-1} = \begin{bmatrix} \alpha_{11} & \alpha_{12} \\ \alpha_{21} & \alpha_{22} \\ \alpha_{31} & \alpha_{32} \end{bmatrix} \begin{bmatrix} \beta_{11} & \beta_{21} & \beta_{31} \\ \beta_{12} & \beta_{22} & \beta_{32} \end{bmatrix} \begin{bmatrix} x_{1,t-1} \\ x_{2,t-1} \\ x_{3,t-1} \end{bmatrix} \\ &= \begin{bmatrix} \alpha_{11}ec_{1,t-1} + \alpha_{12}ec_{2,t-1} \\ \alpha_{21}ec_{1,t-1} + \alpha_{22}ec_{2,t-1} \\ \alpha_{31}ec_{1,t-1} + \alpha_{32}ec_{2,t-1} \end{bmatrix},\end{aligned}$$

where $ec_{1,t-1} = \beta_{11}x_{1,t-1} + \beta_{21}x_{2,t-1} + \beta_{31}x_{3,t-1}$ and $ec_{2,t-1} = \beta_{12}x_{1,t-1} + \beta_{22}x_{2,t-1} + \beta_{32}x_{3,t-1}$. Elements of $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ represent long-run dynamics of the system. The columns of $\boldsymbol{\beta}$ can be interpreted as cointegrating vectors (i.e. parameters of the long-run relations being stationary linear combinations of variables in $\mathbf{x}_t$) , whereas elements of $\boldsymbol{\alpha}$ transfer impact of deviations from long-run equilibrium onto current dynamics of the variables. The matrix $\boldsymbol{\alpha}$ is also sometimes called a *loading matrix*. (Juselius, 2006.)

One important thing to keep in mind is that the factorization $\boldsymbol{\Pi} = \boldsymbol{\alpha}\boldsymbol{\beta}^{'}$ is not unique either. For any $(r \times r)$ nonsingular matrix $\mathbf{H}$ it can be shown that

$$\boldsymbol{\alpha}\boldsymbol{\beta}^{'} = \boldsymbol{\alpha}\mathbf{H}\mathbf{H}^{-1}\boldsymbol{\beta}^{'} = (\boldsymbol{\alpha}\mathbf{H})\left(\boldsymbol{\beta}\mathbf{H}^{-1'}\right)^{'} = \boldsymbol{\alpha}^{*}\boldsymbol{\beta}^{*'}.$$

Obtaining unique values of $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}^{'}$ requires further restrictions on the model.

From VECM, three interesting cases can be distinguished. (1) If the cointegration rank r equals zero, that is $\text{rank}\,(\boldsymbol{\Pi}) = 0$ and the variables collected in $\mathbf{x}_t$ are not integrated, then there are k independent stochastic trends in the system and one can estimate the VAR model in first differences. In that case $\mathbf{x}_{t-1}$ is no longer a regressor in equation (4.10), that is, it is not possible to obtain stationary cointegration relations between the levels of the variables. (2) On the other hand, if $r = k$ then $\text{rank}\,(\boldsymbol{\Pi}) = k$ and each variable taken individually must be stationary. Obviously in that case $k - r$ equals zero and there are no stochastic trends. Then the system can be estimated by applying OLS to unrestricted VAR in levels, or alternatively to equivalent VECM representation. (3) When $0 < r < k$ it is said that $\boldsymbol{\Pi}$ has reduced rank. Then the variables in $\mathbf{x}_t$ are driven by $0 < k - r < k$ common stochastic trends and $\text{rank}\,(\boldsymbol{\Pi}) = r < k$. (Juselius, 2006; Kamps, 2005.)

In case (iii), it is necessary to impose cross-equation restrictions on $\boldsymbol{\Pi}$ and the system cannot be estimated by OLS. Roughly speaking two estimation procedures dominate the cointegration

literature: Johansen's (1988,1991) likelihood-based inference on vector autoregressive error correction models and estimation of Phillips' (1991) triangular forms. The former one has been more popular in practice and shall be used in this thesis.

4.5 Estimation of VECM

Next I will discuss more closely estimation of VECMs. The fact that the asymptotic properties of estimators for non-stationary models differ from those of stationary processes is taken as given here. For example Lütkepohl (2005, Ch 7.1) derives in more detail the asymptotic properties of non-stationary processes. I shall, instead, focus on different estimation methods. I will consider least squares (LS) and ML estimation of the parameters of a VECM model. For the sake of simplicity, only a model without deterministic terms is considered. It can be shown, however, that the computation of the estimators is fairly similar and equally easy even if the deterministic terms are included (Lütkepohl, 2005). Also the estimation of parameters of corresponding levels VAR is discussed shortly in this section.

The model considered here is the same as in (4.10) but without deterministic terms. That is,

$$\triangle \mathbf{x}_t = \mathbf{\Pi}\mathbf{x}_{t-1} + \mathbf{\Gamma}_1 \triangle \mathbf{x}_{t-1} + \mathbf{\Gamma}_2 \triangle \mathbf{x}_{t-2} + \cdots + \mathbf{\Gamma}_{p-1} \triangle \mathbf{x}_{t-p+1} + \boldsymbol{\varepsilon}_t, \tag{4.11}$$

where $\mathbf{x}_t$ is a reduced rank ($rk(\mathbf{\Pi}) = r$ with $0 < r < k$) process of dimension k, so that $\mathbf{\Pi} = \boldsymbol{\alpha}\boldsymbol{\beta}'$ where both $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ are $(k \times r)$ matrices with $rk(\boldsymbol{\alpha}) = rk(\boldsymbol{\beta}) = r$. The error term $\boldsymbol{\varepsilon}_t \sim (\mathbf{0}, \Sigma_\varepsilon)$ is standard white noise. Naturally the process $\mathbf{x}_t$ is assumed to be an unit root process.

It is also necessary to assume that a sample $\mathbf{x}_1, \ldots, \mathbf{x}_T$ as well as the initial values are available. The VECM (4.11) is more convenient to write with shorthand notations so that, for $t = 1, \ldots, T$ the matrix notation is written as

$$\triangle X = \mathbf{\Pi} X_{-1} + \mathbf{\Gamma} \triangle Y + U \tag{4.12}$$

where $\triangle X \coloneqq [\triangle \mathbf{x}_1, \ldots, \triangle \mathbf{x}_T]$, $X_{-1} \coloneqq [\mathbf{x}_0, \ldots, \mathbf{x}_{T-1}]$, $\mathbf{\Gamma} \coloneqq [\mathbf{\Gamma}_1, \ldots, \mathbf{\Gamma}_{p-1}]$ and $\triangle Y \coloneqq [\triangle Y_0, \ldots, \triangle Y_{T-1}]$ with $\triangle Y_{t-1} = [\triangle \mathbf{x}_{t-1} \cdots \triangle \mathbf{x}_{t-p+1}]'$. Moreover, $U \coloneqq [\boldsymbol{\varepsilon}_1, \ldots, \boldsymbol{\varepsilon}_T]$.

4.5.1 Least Squares Estimation

Moving term $\mathbf{\Pi}X_{-1}$ of (4.12) to LHS, for a given matrix $\mathbf{\Pi}$, LS estimator of $\mathbf{\Gamma}$ is obtained from the normal equations $\frac{1}{T}\left(\triangle X - \mathbf{\Pi}X_{t-1}\right)\triangle Y' = \frac{1}{T}\hat{\mathbf{\Gamma}}\triangle Y \triangle Y'$:

$$\hat{\mathbf{\Gamma}} = \left(\triangle X - \mathbf{\Pi}X_{t-1}\right)\triangle Y' \left(\triangle Y \triangle Y'\right)^{-1}.$$

Similarly, LS estimator of $\mathbf{\Pi}$ is written as:

$$\hat{\mathbf{\Pi}} = \left(\triangle X - \mathbf{\Gamma}\triangle Y\right) X_{-1}' \left(X_{-1}X_{-1}^{'}\right)^{-1}.$$

The corresponding white noise covariance matrix estimator is

$$\hat{\Sigma}_u = (T - kp)^{-1}\left(\triangle X - \hat{\mathbf{\Pi}}X_{-1} - \hat{\mathbf{\Gamma}}\triangle Y\right)\left(\triangle X - \hat{\mathbf{\Pi}}X_{-1} - \hat{\mathbf{\Gamma}}\triangle Y\right)'$$

The asymptotic properties of least squares estimators for a VECM are propesed in Lütkepohl (2005, Ch 7). He shows that $\hat{\mathbf{\Gamma}}$, $\hat{\mathbf{\Pi}}$ and $\hat{\Sigma}_u$ are consistent estimators. In particular, he shows that the cointegrating matrix $\boldsymbol{\beta}$ can be known or estimated and yet the asymptotic distribution of estimators of $\mathbf{\Pi}$ and $\mathbf{\Gamma}$ is still the same.

4.5.2 Maximum Likelihood Estimation

For a Gaussian process $\mathbf{x}_t$, the VECM can be estimated by ML taking also the rank restriction for $\mathbf{\Pi} = \boldsymbol{\alpha}\boldsymbol{\beta}'$ into account (Johansen, 1988; Johansen, 1995). As customary in ML estimation, the first step is to derive the log-likelihood function for a sample of size T:

$$\ln l = -\frac{kT}{2}\ln 2\pi - \frac{T}{2}\ln|\Sigma_u| - \frac{1}{2}\mathrm{tr}\left[\left(\triangle X - \boldsymbol{\alpha}\boldsymbol{\beta}' X_{-1} - \mathbf{\Gamma}\triangle Y\right)' \Sigma_u^{-1}\left(\triangle X - \boldsymbol{\alpha}\boldsymbol{\beta}' X_{-1} - \mathbf{\Gamma}\triangle Y\right)\right]. \tag{4.13}$$

One should note especially that ML estimation derived here does not assume that $\boldsymbol{\beta}$ is normalized. The only assumption is related to the rank restriction $rk\left(\mathbf{\Pi}\right) = r$ which implies that the matrix $\mathbf{\Pi}$ can be decomposed into $\mathbf{\Pi} = \boldsymbol{\alpha}\boldsymbol{\beta}'$ (both of dimension $(k \times r)$) with $rk\left(\boldsymbol{\alpha}\right) = rk\left(\boldsymbol{\beta}\right) = r$.

To further simplify the notation, it is defined that

$$\begin{aligned} M &:= I_T - \triangle Y^{'}\left(\triangle Y \triangle Y^{'}\right)^{-1}\triangle Y, \\ R_0 &:= \triangle X M, \\ R_1 &:= X_{-1} M, \end{aligned}$$

and, furthermore, it is defined that for

$$S_{ij} := R_i R_j^{'}/T,\ i = 0, 1,$$

$$\lambda_1 \geq \cdots \geq \lambda_k$$

are the eigenvalues of $S_{11}^{-1/2} S_{10} S_{00}^{-1} S_{01} S_{11}^{-1/2}$, and $\nu_1, \ldots, \nu_k$ are the corresponding orthonormal eigenvectors.

In order to find the maximum of $\ln l$ in (4.13) the result that for any fixed $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ the maximum is known to be

$$\tilde{\boldsymbol{\Gamma}}\left(\boldsymbol{\alpha}\boldsymbol{\beta}^{'}\right) = \left(\triangle X - \boldsymbol{\alpha}\boldsymbol{\beta}^{'} X_{-1}\right)\triangle Y^{'}\left(\triangle Y \triangle Y^{'}\right)^{-1}$$

is utilized. If $\boldsymbol{\Gamma}$ in (4.13) is replaced by $\tilde{\boldsymbol{\Gamma}}\left(\boldsymbol{\alpha}\boldsymbol{\beta}^{'}\right)$, the so-called *concentrated* log-likelihood function is obtained,

$$\ln l = -\frac{kT}{2}\ln 2\pi - \frac{T}{2}\ln|\Sigma_u| - \frac{1}{2}\mathrm{tr}\left[\left(\triangle X\, M - \boldsymbol{\alpha}\boldsymbol{\beta}^{'} X_{-1} M\right)^{'} \Sigma_u^{-1}\left(\triangle X\, M - \boldsymbol{\alpha}\boldsymbol{\beta}^{'} X_{-1} M\right)\right]. \tag{4.14}$$

Now the aim is to maximize expression in (4.14) with respect to $\boldsymbol{\alpha}$, $\boldsymbol{\beta}$ and Σ_u. Using the result (Lütkepohl, 2005 p.295) that for given $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$, Σ_u is substituted by

$$\tilde{\Sigma}\left(\boldsymbol{\alpha}\boldsymbol{\beta}^{'}\right) = \left(\triangle X\, M - \boldsymbol{\alpha}\boldsymbol{\beta}^{'} X_{-1} M\right)\left(\triangle X\, M - \boldsymbol{\alpha}\boldsymbol{\beta}^{'} X_{-1} M\right)^{'}/T,$$

the next step is to maximize

$$-\frac{T}{2}\ln\left|\left(\triangle X\, M - \boldsymbol{\alpha}\boldsymbol{\beta}^{'} X_{-1} M\right)\left(\triangle X\, M - \boldsymbol{\alpha}\boldsymbol{\beta}^{'} X_{-1} M\right)^{'}/T\right| \tag{4.15}$$

with respect to $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$. Equivalently it can be said that the purpose is to find minimum of

the determinant in (4.15). Then

$$\begin{aligned} & \min_{\boldsymbol{\alpha},\boldsymbol{\beta}} |T^{-1}\left(\triangle X\, M - \boldsymbol{\alpha}\boldsymbol{\beta}^{'} X_{-1} M\right)\left(\triangle X\, M - \boldsymbol{\alpha}\boldsymbol{\beta}^{'} X_{-1} M\right)^{'}| \\ = \quad & |T^{-1}\left(\triangle X\, M\right)\left(\triangle X\, M\right)^{'}|\,(1-\lambda_1)\cdots(1-\lambda_r) \end{aligned}$$

and the minimum is attained for

$$\boldsymbol{\beta} = \tilde{\boldsymbol{\beta}} = [\nu_1, \ldots, \nu_r]^{'} S_{11}^{-1/2},$$

$$\boldsymbol{\alpha} = \tilde{\boldsymbol{\alpha}} = \triangle X\, M X_{-p}^{'} \tilde{\boldsymbol{\beta}}\left(\tilde{\boldsymbol{\beta}}^{'} X_{-1} M X_{-1}^{'} \tilde{\boldsymbol{\beta}}\right)^{-1} = S_{01}\tilde{\boldsymbol{\beta}}\left(\tilde{\boldsymbol{\beta}}^{'} S_{11}\tilde{\boldsymbol{\beta}}\right)^{-1}.$$

The minimizing matrices $\tilde{\boldsymbol{\beta}}$ and $\tilde{\boldsymbol{\alpha}}$ are not unique, however. For any non-singular $(r \times r)$ matrix F, $\tilde{\boldsymbol{\alpha}}F^{-1}$ and $\tilde{\boldsymbol{\beta}}F^{'}$ produce another set of ML estimators for $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$. Just to keep in mind, the estimate of $\boldsymbol{\Pi}$ can be derived as $\tilde{\boldsymbol{\Pi}} = \tilde{\boldsymbol{\alpha}}\tilde{\boldsymbol{\beta}}^{'}$.

Furthermore the ML estimates for $\boldsymbol{\Gamma}$ and Σ_u are written as

$$\boldsymbol{\Gamma} = \tilde{\boldsymbol{\Gamma}} \coloneqq \left(\triangle X - \tilde{\boldsymbol{\alpha}}\tilde{\boldsymbol{\beta}}^{'} X_{-1}\right)\triangle Y^{'}\left(\triangle Y \triangle Y^{'}\right)^{-1} \text{ and}$$

$$\Sigma_u = \tilde{\Sigma}_u \coloneqq \left(\triangle X - \tilde{\boldsymbol{\alpha}}\tilde{\boldsymbol{\beta}} X_{-1} - \tilde{\boldsymbol{\Gamma}}\triangle Y\right)\left(\triangle X - \tilde{\boldsymbol{\alpha}}\tilde{\boldsymbol{\beta}} X_{-1} - \tilde{\boldsymbol{\Gamma}}\triangle Y\right)^{'}/T.$$

An estimator of the levels VAR parameters $\mathbf{A}$ (see eq. (4.1)) can be computed also via the estimates of $\boldsymbol{\Pi}$ and $\boldsymbol{\Gamma}$. That can be seen via the relations in (4.10) since $\mathbf{A}_1 = \boldsymbol{\Pi} + \mathbf{I}_K + \boldsymbol{\Gamma}_1$, $\mathbf{A}_i = \boldsymbol{\Gamma}_i - \boldsymbol{\Gamma}_{i-1}$, $i = 2, \ldots, p-1$ and $\mathbf{A}_p = -\boldsymbol{\Gamma}_{p-1}$. Thus the cointegration restrictions can be imposed on the levels version of the estimated VAR process. Imposing no restrictions on $\boldsymbol{\alpha}$ and $\boldsymbol{\Gamma}$ results to situation where the asymptotic distributions of estimator for $\mathbf{A}$ is the same as in (4.6).

4.6 Model Diagnostics

A careful analysis should include checking the validity of a model. Misspecification tests are needed in fact at two stage in empirical part. First when specifying lag length p and fitting the unrestricted VAR model with p lags, and second after fitting the VECM model. A variety of statistical tests exists for this purpose. In this section I will shortly explain how the tests for residual autocorrelation and heteroskedasticity are constructed. I will not, however, focus on normality tests since small sample in this thesis basicly restricts use of most tests. Again

the underlying model is assumed to be of the VECM form, so that

$$\triangle \mathbf{x}_t = \boldsymbol{\alpha}\boldsymbol{\beta}^{'}\mathbf{x}_{t-1} + \boldsymbol{\Gamma}_1\triangle \mathbf{x}_{t-1} + \boldsymbol{\Gamma}_2\triangle \mathbf{x}_{t-2} + \cdots + \boldsymbol{\Gamma}_{p-1}\triangle \mathbf{x}_{t-p+1} + \boldsymbol{\varepsilon}_t, \tag{4.16}$$

where $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ are $(k \times r)$ matrices of rank r and other symbols have same features as defined in (4.10).

4.6.1 Testing Serial Correlation

If there is no autocorrelation between residuals at one point in time and another, it is said that no serial correlation exists. Models usually assume that residuals behave in this way. To check this assumption one can rely on statistical tests such as the Portmanteau statistic or the Breusch-Godfrey LM-statistic (hereafter LM statistic). Both of these tests are applicable also in VECM framework. The estimated residuals of (4.16) are denoted as $\hat{\boldsymbol{\varepsilon}}_t$ and the residual autocovariances as,

$$\hat{C}_i \coloneqq \frac{1}{T}\sum_{t=i+1}^{T} \hat{\boldsymbol{\varepsilon}}_t\hat{\boldsymbol{\varepsilon}}_{t-i}^{'},\ i = 0, 1, \ldots, h.$$

The Portmanteau statistic is defined as

$$Q_h \coloneqq T\sum_{i=1}^{h} \operatorname{tr}\left(\hat{C}_i'\hat{C}_0^{-1}\hat{C}_i\hat{C}_0^{-1}\right)$$

and it has an approximate $\chi^2\left(k^2\left(h-p\right)\right)$ distribution. Also a corrected version for smaller sample sizes and values of h that are not sufficiently large exists in most statistical packages. The corrected test statistic is computed as

$$Q_h^* \coloneqq T^2\sum_{j=1}^{h} \frac{1}{T-j}\operatorname{tr}\left(\hat{C}_i'\hat{C}_0^{-1}\hat{C}_i\hat{C}_0^{-1}\right).$$

The LM statistic for VECM is based upon auxiliary regression model

$$\begin{aligned}\hat{\boldsymbol{\varepsilon}}_t &= \boldsymbol{\alpha}\hat{\boldsymbol{\beta}}^{'}\mathbf{x}_{t-1} + \boldsymbol{\Gamma}_1\triangle \mathbf{x}_{t-1} + \cdots + \boldsymbol{\Gamma}_{p-1}\triangle \mathbf{x}_{t-p+1} \\ &\quad + D_1\hat{\boldsymbol{\varepsilon}}_{t-1} + \cdots + D_h\hat{\boldsymbol{\varepsilon}}_{t-h} + u_t,\ t = 1, \ldots, T,\end{aligned}$$

with $\hat{\boldsymbol{\varepsilon}}_s = 0$ for $s < 1$. The null hypothesis is written as $H_0:\ D_1 = \cdots = D_h = 0$ and the alternative hypothesis as $H_1:\ \exists D_j \neq 0$ for $j = 1, \ldots, h$.

The LM statistic has an asymptotic χ^2-distribution,

$$\lambda_{LM}(h) \xrightarrow{d} \chi^2\left(hk^2\right).$$

Lütkepohl (2005) notes that compared to the Portmanteau test, the LM test is better suitable for testing low order of residual autocorrelation. If h is large, the LM test may fail to estimate the parameters in the auxiliary model due to an insufficient sample size.

Furthermore, a small sample correction for LM test was proposed by Edgerton and Shukur (1999). This corrected statistic is defined as:

$$LM\,F_h \coloneqq \frac{1-\left(1-R_r^2\right)^{1/r}}{\left(1-R_r^2\right)^{1/r}}\frac{Nr-q}{km},$$

with $R_r^2 = 1 - |\tilde{\Sigma}_e|/|\tilde{\Sigma}_R|$, $r = \left(\left(k^2m^2-4\right)/\left(k^2+m^2-5\right)\right)^{1/2}$, $q = 1/2km - 1$ and $N = T - k - m - 1/2\,(k-m+1)$. The number of regressors in the original system defines n, and $m = kh$. This statistic is distributed as $F\left(hk^2, int\,(Nr-q)\right)$.

4.6.2 Testing Heteroskedasticity

Testing for heteroskedasticity in multivariate models corresponds to testing the residuals of the system for heteroskedasticity. Autoregressive conditional heteroskedasticity (ARCH) means that the variation in the residual is conditional on the variable to be modeled. A multivariate ARCH-LM test can be applied for the levels representation of the model to check for ARCH-effects. In general, one would like to find evidence of no ARCH-effects. For testing, a regression model is considered:

$$vech\left(\hat{\boldsymbol{\varepsilon}}_t\hat{\boldsymbol{\varepsilon}}_t^{'}\right) = \boldsymbol{\beta}_0 + B_1 vech\left(\hat{\boldsymbol{\varepsilon}}_{t-1}\hat{\boldsymbol{\varepsilon}}_{t-1}^{'}\right) + \cdots + B_q vech\left(\hat{\boldsymbol{\varepsilon}}_{t-q}\hat{\boldsymbol{\varepsilon}}_{t-q}^{'} + v_t\right) \tag{4.17}$$

where v_t assigns a spherical error process and *vech* is the column-stacking operator for symmetric matrices that stacks the columns from the main diagonal downwards. The matrix $\boldsymbol{\beta}_0$ is $\frac{1}{2}k\,(k+1)$ dimensional and the coefficient matrices B_j, $j = 1, \ldots, q$ are of dimension $\left(\frac{1}{2}k\,(k+1) \times \frac{1}{2}k\,(k+1)\right)$. No ARCH-effect in the residuals corresponds to all B_j matrices being zero. Hence the null and the alternative hypothesis are written as:

$$H_0:\ B_1 = \cdots = B_q = 0 \quad vs. \quad H_1:\ B_1 \neq 0 \,\text{or}\, \cdots \,\text{or}\, B_q \neq 0$$

Now the (multivariate) test statistic is:

$$MARCH_{LM}(q) \coloneqq \frac{1}{2}Tk(k+1)R_m^2,$$

with

$$R_m^2 = 1 - \frac{2}{k(k+1)}\mathrm{tr}\left(\hat{\mathbf{\Omega}}\hat{\mathbf{\Omega}}_0^{-1}\right)'$$

where $\hat{\mathbf{\Omega}}$ is the residuals covariance matrix of the $\frac{1}{2}k(k+1)$ -dimensional regression model and $\hat{\mathbf{\Omega}}_0^{-1}$ is the corresponding matrix with $q = 0$. The statistic has a χ^2 -distribution with degrees of freedom being $qk^2(k+1)^2/4$. Thus for example with $q = 1$ and $k = 4$ the df value is 100.

5 Empirical analysis

In this section I develop separate VAR/VECM models for the Finnish economy and nineteen regions in Finland. By using this approach it is possible to identify the effects of transport infrastructure capital stock on each individual region as well as the regional distribution of the effects of this particular subgroup of public capital formation in a framework that is methodologically in line with the evaluation of the same effects at the aggregate level. Furthermore, I aim to test the existence of regional spillovers by using estimates of effective capital stocks introduced earlier.

The multivariate time series approach addresses to many of the criticisms brought up in the previous literature. The issues related to ignoring time and state effects, the non-stationarity of variables, and the assumption of exogeneity of public capital, might be resolved with a careful consideration. Moreover, testing for the spillover effects on transport infrastructure for Finnish regions might help to deepen the understanding of the spatial and temporal dynamics of the location (of further investment).

The time series properties of the data are studied in this chapter by performing several diagnostic tests. In addition, I estimate a VAR model in levels and an error correction model as well as describe the impulse response functions (IRF). From IRFs the variable elasticities to innovations in transport infrastructure capital variable are estimated.

5.1 Time Series Properties

I use the notation introduced in the previous section on the Finnish data, that is, I express the vector of endogenous variables X_t as $X_t \equiv \left[\begin{array}{cccc} g_t, & p_t, & e_t, & y_t \end{array} \right]'$. Apart from the labour variable the series tend to drift upward over time. I start by exploring whether the individual series are stationary or not. The most commonly used tests for assessing the order of integration of certain time series are probably Dickey-Fuller (1979)(DF) test, the Augmented Dickey-Fuller (Said and Dickey, 1984)(ADF) test, Perron-Phillips (1988)(PP) test and Kwiatkowski-Phillips-Schmidt-Shinn (1992)(KPSS) test. The DF, ADF and PP tests test the null of unit root whereas KPSS test is designed testing the null that observed series is stationary around a deterministic trend. To get a clear picture of stationarity properties of each variable, I choose to cross-check. In other words, I involve in the analysis a test for which the null hypothesis is non-stationarity (the ADF test) as well as a test for which the null is stationarity (the KPSS test).

Kwiatkowski et al. (1992) point out that standard unit root tests often fail to reject the null hypothesis of a unit root for many economic time series. This is especially true for "near unit root" processes, i.e. when the autoregressive parameter is close to but lower than one. To tackle with this problem they suggest that "it would be useful to have available tests of null hypothesis of stationarity as well as tests of the null hypothesis of a unit root". By testing both the unit root and the stationarity hypothesis, one can distinguish series that appear to be stationary, series that appear to be non-stationary (i.e. have a unit root) or series for which the data are not informative enough to be sure whether they are stationary or integrated. To test the null hypothesis of stationarity against the alternative of a unit root, they use a components representation in which the time series examined is written as the sum of a deterministic trend, a random walk, and a stationary error. Then the null hypothesis of trend stationarity corresponds to the hypothesis that the variance of the random walk equals zero. Also the null hypothesis of level stationarity can be tested similarly. (Kwiatkowski et al., 1992.)

Moreover, panel unit root tests, namely tests introduced by Maddala and Wu (1999)(MW), Im, Pesaran and Shin (1997)(IPS), and Levin, Lin and Chu (1993)(LLC) are implemented since some authors (for example Eriksson, 2005) have argued that using panel data unit root tests might be one way of increasing the power of unit root tests based on a single time series. The advantage of panel data is that it combines information from the time series dimension with that obtained from the cross-sectional. In some environments taking into account the cross-section dimension makes the inference about the existence of unit roots and cointegration more precise.

Maddala and Wu (1999) criticized earlier panet unit root tests, especially tests by Levin and Lin (1993) as well as Im, Pesaran and Shin (1997), for especially three reasons. First, those tests do not allow for unbalanced panels (meaning not having same T for every unit). Second, their critical values are sensitive to the choice of lag lengths in the ADF regressions. Third, they assume too simple form of cross-correlation across units. As sort of a proposal of improvement Maddala and Wu (1999) introduce the use of the Fisher (p_λ) test which is based on combining the p-values of the test statistic for a unit for in each cross-sectional unit. MW test can be performed with any unit root test on a single time series. Also the MW test does not require using the same unit root test in each cross section.

For panel tests, a common null hypothesis is that all individual series contain a unit root (this is the case for at least MW, IPS and LLC tests). The alternative hypothesis is usually stated as that all individual units are stationary or that there are some stationary individual units.

I start by conducting ADF tests for series of each variable at both national and regional level. The number of lags included in the test regression is determined by Akaike Information Criterion (AIC). Also the deterministic components (constant and trend) are included if they are statistically significant. Moreover, I test the first difference series in order to examine if the level series can be safely classified as $I(1)$ variables. Results for ADF tests of national series are presented in Table 3. Results for the regional counterparts are presented in Appendix.

The results in Table 3 are mostly in line. The null hypothesis of a unit root at 5 % critical level should not be rejected for any of the variables. Thus aggregate series seem to contain a unit root. The first difference series reject (except for p) the null at all significance levels, indicating that variables are indeed $I(1)$. I continue to testing the null of stationarity with the KPSS test (results in Table 4). These results point to the direction that the null of stationarity should be rejected. In other words, it seems that according to KPSS test all aggregate series are non-stationary. Also for the regional series the results of ADF tests (Appendix) provide evidence of non-stationarity. I have not tested the effective capital series $\left(g^{eff}\right)$ separately since they are simply combinations of g^{in} series and, consequently, likely behave in same manner.

Results from panel unit root tests are presented in Table 5. Compared to individual unit root tests these results are rather confounding since different tests produce very heterogenous results. Keeping the null indicates that all series should be treated as unit root series. It seems that labour series is the one that contains most evidently a unit root. Also for other variables at least one of the tests implemented indicates that the null should not be rejected.

Considering the short time span of the time series used as well as taking into account the robustness problems of unit root tests, it seems plausible to continue treating all series as $I(1)$.

Variable	Deterministic terms	Lags	Test value	Critical values		
				1%	5%	10%
y	constant, trend	2	-1.90	-4.15	-3.50	-3.18
Δy	constant	1	-3.54	-3.58	-2.93	-2.60
e	constant, trend	2	-2.20	-4.15	-3.50	-3.18
Δe	constant	1	-3.54	-3.58	-2.93	-2.60
p	constant, trend	2	-2.37	-4.15	-3.50	-3.18
Δp	constant	0	-2.24	-3.58	-2.93	-2.60
g	constant, trend	2	-0.83	-4.15	-3.50	-3.18
Δg	constant	1	-3.46	-3.58	-2.93	-2.60

Table 3: ADF tests for Finnish data

Region	Variable	KPSS trend	p-value
Finland	y	0.1757	0.0253*
	e	0.1551	0.0424*
	p	0.2904	0.01**
	g	0.2596	0.01**
Uusimaa	y	0.1684	0.0314*
	e	0.1605	0.0379*
	p	0.2753	0.01**
	g	0.3308	0.01**
Kanta-Häme	y	0.1748	0.0260*
	e	0.1471	0.0491*
	p	0.2443	0.01**
	g	0.3984	0.01**

Note: An asterisk (*) indicates that the test is rejected at the 5 % significance level. A double asterisk (**) indicates rejection at the 1 % significance level.

Table 4: KPSS tests for national and selected regional data

Variable	Test	Test statistic	p-value
	Maddala-Wu	χ^2	
y		41.3855	0.3251
e		25.921	0.9317
p		140.0582	0**
g		74.6328	0.0004**
	Im-Pesaran-Shin		
y		3.6551	0.0003**
e		-1.687	0.09155
p		-1.801	0.07163
g		2.203	0.02759*
	Levin-Lin-Chu		
y		0.3756	0.7072
e		-3.1332	0.00173**
p		-4.1806	0**
g		-2.4888	0.01282**

Note: An asterisk (*) indicates that the test is rejected at the 5 % significance level. A double asterisk (**) indicates rejection at the 1 % significance level.

Table 5: Results for panel unit root tests

5.2 Building the Model

The lag order, the cointegration rank and possible restrictions have to be determined in specifying VECMs. The model building usually starts by determining the suitable lag order since order selection does not require any knowledge of the cointegration rank whereas the opposite is not true. After finding the lag order I will continue with determination of the cointegration rank. Finally model estimations are considered.

I shall stress out that for each Finnish region, two separate models are build. The first one includes transport infrastructure capital stock located within the region itself, g_t^{in}, as a first variable in the vector of endogenous variables, and the second one includes the estimated effective transport infrastructure capital stock, g_t^{eff}, as a first variable. I will denote the regional systems as $Y_t^{1,i} = \left[\begin{array}{cccc} g_{t,}^{in,i}, & p_{t,}^{i}, & e_{t,}^{i}, & y_t^i \end{array} \right]'$ and $Y_t^{2,i} = \left[\begin{array}{cccc} g_t^{eff,i}, & p_t^i, & e_t^i, & y_t^i \end{array} \right]'$ for $i = 1, \ldots, N$. The results reported in this section focus on the systems $Y_t^{1,i}$. The models are build in similar manner also for $Y_t^{2,i}$.

5.2.1 VAR Order Selection

The lag order p is typically unknown in empirical applications. Determination of the optimal lag order should be based on some sort of *selection criteria*. The selection criteria I consider in my analysis are (1) the Akaike (1973) information criterion (AIC), (2) the Schwarz (1978) information criterion (SC), and (3) the Hannan and Quinn (1979) information criterion (HQ).

For a $k-$dimensional VAR(p) process they are defined by:

$$\begin{aligned} AIC\left(p\right) &= \ln|\overline{\sum}_u\left(p\right)| + \frac{2}{T}\left(k^2 p\right), \\ SC\left(p\right) &= \ln|\overline{\sum}_u\left(p\right)| + \frac{\ln T}{T}\left(k^2 p\right), \\ HQ\left(p\right) &= \ln|\overline{\sum}_u\left(p\right)| + \frac{2\ln\,\ln T}{T}\left(k^2 p\right), \end{aligned}$$

where T is the sample size and $\overline{\sum}_u$ the maximum likelihood estimate of $\sum_u$. Thus they are all based on the maximal value of the likelihood function with an additional penalizing factor related to the number of estimated parameters. The lag order $\hat{p}$ is chosen to minimize the value of the criterion over a range of alternative lag orders given by $\{p : \ 1 \leq p \leq \bar{p}\}$. This time I set maximum number of lags to four, $\bar{p} = 4$.

The first columns of Table 6 present the optimal lag order selected by the three criteria for each region considered. In general, AIC and HQ select a higher lag order than the SC criteria.

Considering the small sample size I am restricted to, choosing a parsimonious specification of the model seems like a good guideline. Also the anticipatory use of VECM narrows down number of choices ($p = 1$ is not an option anymore). Chosen lag order is reported in column five in Table 6. Moreover Table 6 gives results for specification tests that check whether for the chosen lag length the residuals are non-autocorrelated and homoskedastic. The specification tests are based on the residuals from the estimation of an unrestricted VAR(p), where p is the chosen VAR order reported in column five. I use a small sample correction for LM proposed by Edgerton and Shukur (1999) and ARCH-LM test (both presented in Section 4) and the results of specification tests are found in columns six and seven. Results indicate that the residuals can be classified as homoskedastic as well as free from first-order autocorrelation. The only exception is region of Etelä-Pohjanmaa, for which at 5 % significance level the null of no residual autocorrelation is rejected. Increasing lag order should solve the problem of residual autocorrelation, thus lag order of Etelä-Pohjanmaa is increased to $p = 3$. Testing for normality would be a standard as well but sample used in this thesis is too small to use to regular normality tests. The null of normality of residuals was turned down by all tests. A visual inspection in the form of QQ-plots was done instead.

	VAR order min.				Specification tests (p-values)	
Region	AIC	SC	HQ	Chosen	LMF test	$ARCH - LM$ test
Finland	2	1	2	2	0.415	0.238
Uusimaa	2	2	2	2	0.242	0.374
Varsinais-Suomi	3	1	3	3	0.297	0.329
Satakunta	1	1	1	2	0.106	0.238
Kanta-Häme	1	1	1	2	0.622	0.237
Pirkanmaa	2	2	2	2	0.014	0.490
Päijät-Häme	2	1	1	2	0.420	0.349
Kymenlaakso	1	1	1	2	0.457	0.438
Etelä-Karjala	2	1	2	2	0.561	0.460
Etelä-Savo	3	1	3	3	0.832	0.151
Pohjois-Savo	3	1	1	3	0.604	0.180
Pohjois-Karjala	3	1	3	3	0.115	0.101
Keski-Suomi	3	1	3	3	0.332	0.281
Etelä-Pohjanmaa	1	1	1	2	0.019	0.335
Pohjanmaa	3	1	3	3	0.702	0.471
Keski-Pohjanmaa	3	1	3	3	0.177	0.412
Pohjois-Pohjanmaa	3	1	3	3	0.139	0.323
Kainuu	2	1	2	2	0.297	0.293
Lappi	3	1	1	3	0.736	0.333
Itä-Uusimaa	3	1	1	3	0.266	0.406

Table 6: Specification of VAR orders

5.2.2 Testing Cointegration Rank

Once the variables have been classified as integrated of order $I(1)$, it is possible to set up models that lead to stationary relations among them. If the system includes cointegrating relations, IRFs from VAR model in levels without explicitly considering cointegration leads to inconsistent estimates of responses for long horizons as well as incorrect confidence intervals. The Johansen (1988, 1991) test procedure seems like the most suitable one for testing cointegration among variables for this thesis. In contrary to Engle-Granger (1987) type residual based tests[9], the Johansen test produce allows the existence of more than one cointegrating relations. For example Batina (1998) has found evidence of multiple cointegrating vectors while examining the cointegration properties of data on aggregate output, labour, private capital and (disaggregated) public capital. However, Batina (1998) also points out that there is much less evidence for cointegration when public capital is disaggregated into real spending on on highways and streets and real spending on water and sewer systems. Also the neoclassical growth theory suggests that along the balanced growth path variables such as output, capital, consumption, and investment grow at the same constant rate, giving an incentive to test for several cointegrating relations (Kamps, 2005).

The Johansen method for cointegration analysis is concerned with the matrix $\mathbf{\Pi}$ in the vector error correction model (eq. 4.10). In a cointegrated model it can be decomposed into two matrices, α and β , as $\mathbf{\Pi} = \alpha\beta'$. Both α and β have the same dimension, $(k \times r)$, where r is the number of cointegrated relations in the model. As explained earlier, the matrices α and β can be interpreted followingly: β is a matrix of long-run cointegration relations and the elements in α are adjustment coefficients, which determine the speed of adjustment back to equilibrium after a deviation from the long-run relation. (Eriksson, 2006.)

Details about the estimation procedure can be found in Johansen (1988). To summarise the procedure is following an algorithm of three steps to estimate the maximum likelihood of the model parameters and identification of the cointegration relations. The procedure enables determination of the cointegration rank r with two tests, the *maximum eigenvalue test*, and the *trace test*. I use the trace test in my analysis and it is given by

$$\mathrm{LRT_{TT}} = -T \sum_{i=r+1}^{n} log\left(1 - \hat{\lambda}_i\right), \tag{5.1}$$

[9]Residual based tests for cointegration proceed by estimating an equation and after that, they test the residuals for stationarity using either the Augmented Dickey Fuller test or the Phillips-Perron test for unit roots. Stationary residuals contain evidence of cointegration among the variables included in the regression equation. (See e.g. Batina, 1998.)

where $\hat{\lambda}_i$ are the eigenvalues of the Π-matrix estimated under the null hypothesis. When using the trace test, the testing sequence can be expressed followingly:

$$H_0\left(r_0\right):\ rank\left(\mathbf{\Pi}\right)=r_0 \quad vs. \quad H_1\left(r_0\right):\ rank\left(\mathbf{\Pi}\right)=k,\ r_0=0,\ 1,\ 2,\ 3.$$

In other words, the trace test is testing $H_0 : r_0$ is the number of cointegrating relations versus $H_1 : k$ is the number of cointegrating relations. If the test statistic is greater than the critical values (see Table 7), H_0 is rejected. Starting with the null hypothesis that the cointegration rank is zero, if the hypothesis is rejected, there is evidence that there exists at least one cointegrating relation. Continuing the procedure until the null hypothesis is not rejected, one can determine the total number of cointegrating relations in the system. The results for Johansen trace tests for the Finnish data can be seen in Table 7. Testing for $p = 2$ since it has been examined to be the appropriate number of lags for national level model in previous section, the null is rejected at the first round ($r = 0$) for all significance levels. Continuing further we reject the null $r = 1$ and $r = 2$ for both lag lengths at 5 % significance level. On the next round test statistic is smaller than the 5 % value. Thus the testing procedure is stopped here and it can be concluded that number of cointegrating relations for national level data is three.

As a deterministic term, a linear trend in cointegration relations is considered. Constant is left unrestricted, as suggested by Kamps (2005). I have also included an exogenous dummy variable in my models. Purpose of the dummy is to account for unplausibly large changes (or shocks) in transport infrastructure capital stock series (as seen in Figure 1). For national level series a larger than 10 % increase in level series is considered as an usually large change, whereas for regional level series the threshold value is 5 %.

	Eigenvalue	Trace Statistic	Critical value
H_0	λ	$p = 2$	95%
$r = 0$	0.850	102.82	62.99
$r = 1$	0.562	49.71	42.44
$r = 2$	0.483	26.60	25.32
$r = 3$	0.252	8.14	12.25

Table 7: The eigenvalues, trace statistic, and 95 % quantiles for national data

Same testing procedure is repeated for the regional data. From Table 8 it can be seen that cointegration rank for majority of regions is two or three. I use this information and estimate VECMs for regions imposing the appropriate rank restriction. For regions with rank zero a

VAR in first differences would be a suitable choice instead, and for regions with rank four a VAR in levels. For two regions, namely Pohjois-Savo and Kainuu, the suggested number of cointegrating relations according to trace test is four, indicating that VAR in levels is a more suitable choice. I have, however, chosen $r = 3$ for both regions since the trace statistic is close to the 5 % critical value and under the 1 % critical value.

		Trace statistic				
Region	VAR order	H_0:$r = 0$	H_0:$r = 1$	H_0:$r = 2$	H_0:$r = 3$	Rank
Uusimaa	2	83.07	36.57	12.57	1.69	1
Varsinais-Suomi	3	105.42	60.04	27.16	8.42	3
Satakunta	2	74.13	41.52	16.53	4.37	1
Kanta-Häme	2	76.68	46.47	22.23	5.10	2
Pirkanmaa	2	69.38	31.97	12.35	0.60	1
Päijät-Häme	2	86.10	45.81	24.01	8.51	2
Kymenlaakso	2	68.54	39.83	17.64	3.70	1
Etelä-Karjala	2	106.25	44.66	18.94	6.25	2
Etelä-Savo	3	181.06	83.91	36.56	11.38	3
Pohjois-Savo	3	113.40	58.30	32.42	12.47	3*
Pohjois-Karjala	3	100.16	44.91	24.01	4.37	2
Keski-Suomi	3	124.93	50.66	25.83	10.12	3
Etelä-Pohjanmaa	3	101.19	58.72	33.92	10.90	3
Pohjanmaa	3	89.61	50.70	22.13	7.63	2
Keski-Pohjanmaa	3	102.94	47.02	14.64	1.59	2
Pohjois-Pohjanmaa	3	84.41	35.98	20.79	8.32	1
Kainuu	2	109.14	64.90	26.57	12.30	3*
Lappi	3	79.21	43.21	18.46	1.20	2
Itä-Uusimaa	3	83.51	45.02	24.81	8.50	2

Table 8: Johansen cointegration tests for Finnish regions

5.2.3 VECM Estimations

The questions of appropriate lag length and cointegration rank have already been examined and now I exploit that information in VECM estimations and try to make some interpretations about the estimated coefficients. Thus the aim is to analyse the dynamics of the transport infrastructure capital stock variable with the remaining variables from the estimated coefficients of restricted VECM. The coefficients are estimated by OLS and therefore the interpretation is the same as in an ordinary least squares regression.

Focusing on the national level model, the model specifications are based on what we have already learned. Number of chosen lags is $p = 2$ and the number of cointegrating relations

$r = 3$, meaning that the national level model is now written as,

$$\triangle \mathbf{x}_t = \mathbf{\Pi}_1 \mathbf{x}_{t-1} + \mathbf{\Pi}_2 \mathbf{x}_{t-1} + \mathbf{\Pi}_3 \mathbf{x}_{t-1} + \mathbf{\Phi} \mathbf{D}_t + \mathbf{\Gamma}_1 \triangle \mathbf{x}_{t-1} + \mathbf{u}_t,$$

where deterministic term includes a constant and a dummy for transport infrastructure capital shocks as explained earlier. The coefficients of the national level VECM are presented in Table 9 and the normalized cointegrating vectors in Table 10. A first glance from Table 9 validates the concerns about the full exogeneity of transport infrastructure capital since both first lag of private capital stock variable and first lag of labour variable are significant coefficients. Furthermore, Table 9 indicates that the first lag of transport infrastructure variable is highly significant in labour and output equations. For both equations the coefficient is negative, implying that increasing transport infrastructure capital stock decreases output and number of workers. In all of the equations at least one of the error correction terms is significant, supporting the basis that a long-run relationship exists between the model variables.

Coefficient	Variable			
	g	p	e	y
ect1	0.0910	0.1820	-0.5038***	-0.8603**
ect2	-0.1458***	-0.2440**	0.2471*	0.2077
ect3	0.1472*	0.4227**	-0.3468	0.000
constant	-1.0023	-2.1714	7.4780***	13.81*
Pub.shock	-0.1307***	0.0215	0.0312*	0.0585
g.dl1	0.0806**	0.0134	-0.6328***	-1.092***
p.dl1	-0.4093***	0.2267	0.2341	0.2849
e.dl1	0.1885*	0.6523***	0.4596	0.6769
y.dl1	-0.0596	-0.0703	0.0166	-0.4101

Note: An asterisk (*) indicates that the coefficient is significant at the 10 % level. A double asterisk (**) indicates significance at the 5 % level, and a triple asterisk (***) at the 1 % level.

Table 9: Coefficient matrix of the national level restricted VECM

	Ect 1	Ect 2	Ect 3
g.l2	1	0	0
p.l2	0	1	0
e.l2	0	0	1
y.l2	0.545	-0.927	-1.377
trend.l2	-0.028	0.020	0.040

Table 10: Normalized cointegrating vectors, national level restricted VECM

From regional level models I will concentrate here on two selected regions to illustrate how

within-region models and spillover models might differ from each other. I have chosen the most geographically central region (Uusimaa, estimation results in Table 11) and one peripheral region (Etelä-Savo, estimation results in Table 12) in order to accentuate the role of spillover effects for geographically more distant regions.

Coefficient	Variable			
	Model 1			
	g^{in}	p	e	y
ect1	0.124	0.247	-0.142	-1.910***
constant	-1.497	-3.125	1.766	24.051***
Pub.shock	-0.063***	0.018	0.047*	0.133***
g.dl1	0.262*	-0.226	-1.026***	-2.332***
p.dl1	-0.110	0.514**	0.113	1.480***
e.dl1	0.067	0.046	0.572**	0.985***
y.dl1	-0.058	0.196	0.085	-0.766***
	Model 2			
	g^{eff}	p	e	y
ect1	0.133	0.223	-0.218	-1.938***
constant	-1.672	-2.952	2.841	25.472***
Pub.shock	-0.074***	0.018	0.053**	0.143***
g.dl1	0.224*	-0.205	-1.031***	-2.254***
p.dl1	-0.140	0.514**	0.223	1.727***
e.dl1	0.077	0.077	0.565**	0.771***
y.dl1	-0.050	0.186	0.062	-0.739***

Note: An asterisk (*) indicates that the coefficient is significant at the 10 % level. A double asterisk (**) indicates significance at the 5 % level, and a triple asterisk (***) at the 1 % level.

Table 11: Coefficient matrices of Uusimaa model estimations

It seems that for Uusimaa both within-region and effective transport infrastructure capital stocks are fairly exogenous variables in models since they are explained only by their own lagged values. In output equations, on the other hand, all model variables are significant at least on 5 % significance level. Moreover, the estimated coefficients are very similar in both models, indicating that changes in outside-region transport infrastructure capital stock does not have a great impact on levels of output, private capital and labour variables at Uusimaa. The results of Etelä-Savo models presented in Table 12 show more variation between model estimates. The within-region transport infrastructure capital variable is explained by its own lagged values as well as lagged values of labour and output variables. The effective transport infrastructure capital is not explained significantly by any of the model variables, not even by its own lagged values. Interestingly, the second lag of effective transport infrastructure

variable seems to have a stronger explanatory power than the first lag. Thus responses to changes in outside-region transport infrastructure capital stock are slower yet by no means totally insignificant.

Coefficient	Variable			
	Model 1			
	g^{in}	p	e	y
ect1	0.549***	-0.112***	-0.222***	-0.229
ect2	0.316*	-0.319***	0.557***	0.459
ect3	0.795***	0.112	-1.543***	-1.485*
constant	-12.196***	1.721*	13.034***	13.335**
Pub.shock	-0.238***	0.005	-0.030***	-0.063*
g.dl1	-0.772***	0.090**	-0.0516	-0.180
p.dl1	0.792	-0.693**	1.459***	1.702
e.dl1	0.395*	0.253**	-0.615***	-0.542
y.dl1	-0.239**	-0.097	-0.235**	-0.358
g.dl2	-0.567***	-0.002	-0.306***	-0.256
p.dl2	0.782	-0.065	1.863***	1.345
e.dl2	0.542**	0.203	-1.158***	-1.335*
y.dl2	-0.225*	-0.052	0.144	0.053
	Model 2			
	g^{eff}	p	e	y
ect1	-0.041	-0.097	-1.492***	-1.949***
ect2	0.068	-0.328***	0.724***	0.823*
constant	0.915	-0.111	24.074***	30.923***
Pub.shock	-0.030**	-0.020***	-0.029***	-0.057**
g.dl1	-0.050	0.047	-0.146	-0.322
p.dl1	0.160	-0.510**	0.726**	0.910
e.dl1	-0.082	0.410***	-0.778***	-1.004
y.dl1	-0.074	-0.130*	-0.162*	-0.245
g.dl2	0.234	-0.232**	-0.964***	-0.670
p.dl2	0.381	-0.319	1.166***	0.979
e.dl2	-0.110	0.249*	-1.111***	-1.333**
y.dl2	0.060	-0.019	0.114	-0.065

Note: An asterisk (*) indicates that the coefficient is significant at the 10 % level. A double asterisk (**) indicates significance at the 5 % level, and a triple asterisk (***) at the 1 % level.

Table 12: Coefficient matrices of Etelä-Savo model estimations

5.3 Impulse Response Analysis

5.3.1 Orthogonalization and Cholesky Decomposition

The scope of this thesis is to investigate how the variables in the system react to shocks in transport capital stock variable. So far the analysis has focused on studying the interaction between the variables in a VAR/VECM framework. Already from these models it is possible to draw some conclusions about how one variable react to changes in the other variables at other points in time. Getting a clear picture of the dynamics from model coefficients can be challenging though. That is why computing Impulse Response Functions (IRFs) comes in helpful. IRF tells how a variable i reacts to a shock in variable j at time t over the time period from t to $t+h$, where h is the chosen forecast horizon.

For a VAR model of the form (4.1), and assuming that the process is stationary, the IRF can be derived from infinite moving average (MA(∞)) process,

$$\mathbf{y}_t = \Phi_0 u_t + \mathbf{\Phi}_1 \mathbf{u}_{t-1} + \cdots , \tag{5.2}$$

where $\Phi_0 = I_n$ and $\mathbf{\Phi}_s = \sum_{j=1}^{s} \mathbf{\Phi}_{s-j} A_j$, $s = 1, 2, \ldots$, can be calculated recursively from the coefficients of the VAR in levels. In this form (also called the Wold moving average representation) changes in $\mathbf{u}_t$ are the impulses and the $\mathbf{\Phi}$s reflect how the system responds to them.

For a non-stationary process, it is plausible to assume that the off-diagonal elements of the variance-covariance matrix $\sum_u$ are not null and the impulses measured by the $\mathbf{\Phi}_s$ matrices would also reflect disturbances from other variables. Thus orthogonalization is required if we want to analyse the impact of an isolated shock. A Cholesky decomposition by considering $\sum_u = PP'$, where P is a lower triangular matrix, is often used in practice. Then the orthogonal shocks are given by $\varepsilon_t = P^{-1} u_t$ and the moving average presentation (5.2) can be written as

$$\mathbf{y}_t = \mathbf{\Psi}_0 \boldsymbol{\epsilon}_t + \mathbf{\Psi}_1 \boldsymbol{\epsilon}_{t-1} + \cdots , \tag{5.3}$$

with the matrices $\mathbf{\Psi}_s$ computed as $\mathbf{\Psi}_s = \mathbf{\Phi}_s P$ for $s = 1, 2, 3, \ldots$. One can see that $\mathbf{\Psi}_0 = \mathbf{I}_n P$, which means that a shock ϵ in the first variable has an instantaneous effect on all variables, second one on the variables excluding the first one and so on. This means that variables take a causal order where a variable cannot (directly) affect the variables coming before itself. In

this case the IRF is written followingly:

$$IRF_{i,j} = \frac{\partial y_{i,t+s}}{\partial \epsilon_{j,t}} = \frac{\partial y_{i,t}}{\partial \epsilon_{j,t-s}} = \mathbf{\Psi}_s. \tag{5.4}$$

5.3.2 Identifying Assumptions

Variable ordering is in a key role when building the model if one wants to give the impulse response functions a structural interpretation. Following the 'standard' way in the literature (Pereira & Roca-Sagalés, 2003; Kamps, 2005; Marquéz et al., 2011), I state four assumptions required for the exact identification of the structural errors: (1) innovations in transport infrastructure investment affect contemporaneously private capital, employment and real output, whereas the reverse is not true; (2) shocks to private capital affect contemporaneously employment and real output, whereas the reverse is not true; (3) employment does not react contemporaneously to shocks to real output, but is affected contemporaneously by shocks to both public and private capital, and finally; (4) real output is affected contemporaneously by shocks to all other variables in the system. Thus the relation between the reduced-form disturbances and the structural disturbances takes the following form:

$$\begin{bmatrix} 1 & 0 & 0 & 0 \\ a_{21} & 1 & 0 & 0 \\ a_{31} & a_{32} & 1 & 0 \\ a_{41} & a_{42} & a_{43} & 1 \end{bmatrix} \begin{bmatrix} \varepsilon_t^g \\ \varepsilon_t^p \\ \varepsilon_t^e \\ \varepsilon_t^y \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} e_t^g \\ e_t^p \\ e_t^e \\ e_t^y \end{bmatrix}.$$

The identifying assumptions can be explained in numerous ways but for example Kamps (2005) and Pereira and Roca-Sagalés (2003) provide a sensible enough justification for this case (another option would be to test decreasing order of exogeneity among variables by using bivariate Granger causality tests). First of all, movements in government spending are largely unrelated the business cycle, due to the time lag deriving from public decision making and implementation. Hence it seems rational to assume that public is not affected contemporaneously by shocks from the private sector. Also private capital can be seen as unrelated to the business cycle. Employment in general lags the business cycle[10] and that is why I assume that it is unaffected contemporaneously by output shocks. Placing real ouput as a last variable stems from a general form of a production function, which indicates that the three inputs affect output variable contemporaneously.

[10]See e.g. Stock and Watson (1999) for US macroeconomic time series.

For regional models the ordering of the variables is the same as for national level model. The effective transport infrastructure capital stock can be considered even more clearly as the most exogenous variable since most of the decisions concerning outside-region transport infrastructure investment cannot be affected by the region itself. Also the results from VECM estimations support this assumption.

5.3.3 Results

Impulse responses to a shock to transport infrastructure capital in national level model are presented in Figure 3. For identification of the model I use a Cholesky decomposition of the residual covariance matrix and the variables are in order motivated above. The solid lines present a point estimate of the impulse responses and the dotted lines present 68 % bootstrap confidence intervals[11]. The shock to transport infrastructure capital has size of one unit (which is the default in vars package). Figure 3 implies that the dynamic effects of a shock to g are negative. Significance of the responses is simply determined by the bootstrapped 68 % confidence interval. If this interval does not include value zero, the response is considered as significant. As can be seen from Figure 3, my results are not highly significant. There is, however, a similar pattern in IRFs for labour and output variables. The responses are negative, indicating that output and labour are substitutes to transport infrastructure capital. It seems that in short-run, the crowding-out effect is more clearly present than in the medium-run for these variables. Private capital and transport infrastructure are weakly complementary in short-run but substitutes after period four.

One way to investigate the IRFs in this context is to assume that a neoclassical production function is a valid description of the relation between the variables. Then responses of all other variables taken together should explain the observed pattern of output responses. It can be seen from Figure 3 that for the national level model the impulse responses of labour and private capital provide support to this idea. The responses of transport infrastructure capital are, in contrary, positive for the entire horizon. Negative output responses are reconciled with positive transport infrastructure responses only if the marginal productivity of transport infrastructure is negative. That would of course indicate that the transport infrastructure to output ratio is beyond its optimal level.

[11] Impulse responses are random variables and thus providing confidence intervals is in order. The bootstrap method is based on taking M resamples of size m from the original sample to estimate the sample distribution. An example how a simple bootstrap algorithm is constructed can be found in Kamps (2005). Choosing $\alpha = 0.16$ in calculating the α and $1 - \alpha$ percentile interval endpoints of the distribution corresponds to 68 % confidence intervals. In statistical inference the 68 % confidence interval marks the values that lie within one standard deviations of the mean (point estimate).

In Figure 4 each subplot displays an output response from a shock to g^{in} for Finnish regions. These output respones can also be interpreted as *direct effects*. Across regions the results from national level model repeat themselves. In general, the output response is negative and the impulse responses are estimated quite imprecisely. It seems that the crowding-out effect in short-run is especially strong on those regions which exhibit low rank for the ratio of GDP over transport infrastructure capital stock (Pohjois-Karjala, Kanta-Häme, Etelä-Savo and Uusimaa, for example). However, even for regions with one of the highest ranks on the ratio, the responses are similar or in some cases even more clearly negative. For example Pohjois-Savo region has low endowment of transport infrastructure compared to many other regions, yet the output response to a shock to transport infrastructure capital stock is significantly negative.

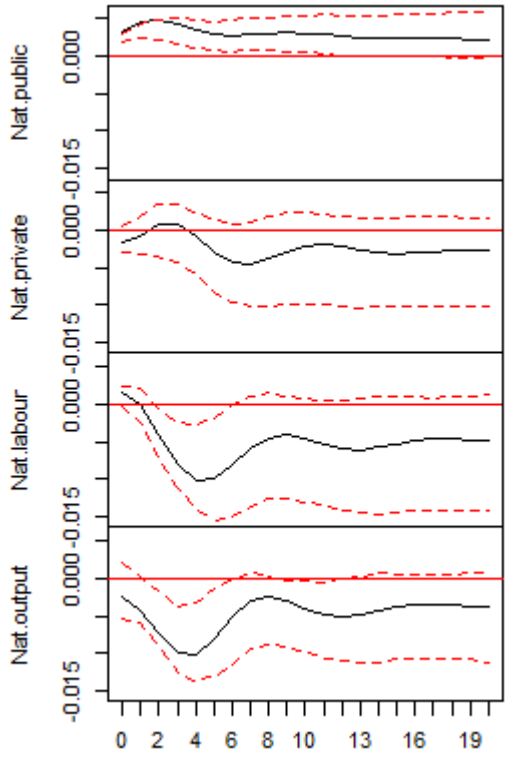

Figure 3: Impulse responses to a shock to transport infrastructure capital on national level. Variables from the top: Transport infrastructure capital stock, Private capital stock, Labour and GDP.

As explained earlier, on regional level two models are estimated for each region in order to test if spillover effects exist. In Figure 5 each subplot presents an output response from a shock to g^{eff}. So the IRFs in Figure 5 present how output in a particular region reacts to a shock to the estimated effective transport infrastructure capital stock. Noteworthily, for many regions the

pattern of responses over examined horizon remains the same. Again some exceptions can be pointed out. For example region of Pohjanmaa displays a surprisingly strong positive output response when the effective transport infrastructure capital stock is used instead of inside-region capital stock. All in all, it seems that output responses are most similar in magnitude and pattern for Uusimaa which is geographically the most central region in Finland. The peripheral regions, on the other hand, show tendency to more intense spillover effects. By this I refer to greater magnitude of responses as well as to different response patterns.

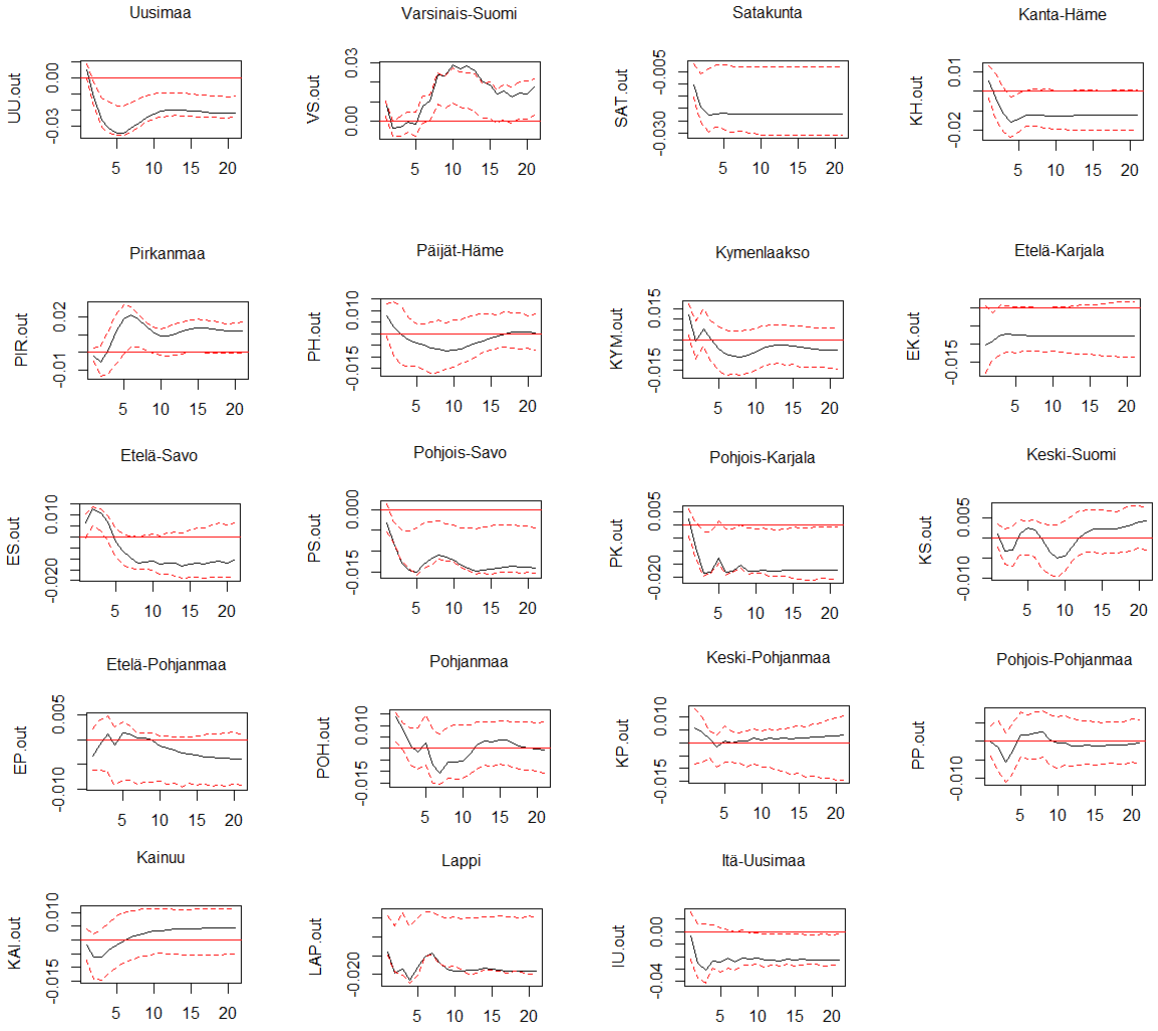

Figure 4: Output responses to a shock to g^{in}

For a quantitative comparison across regions I calculate long-run elasticities that are presented in Table 13. Long-run is now defined as a time horizon at the end of which the effects of a shock vanish. I consider a horizon of fifty periods which according to visual inspection should

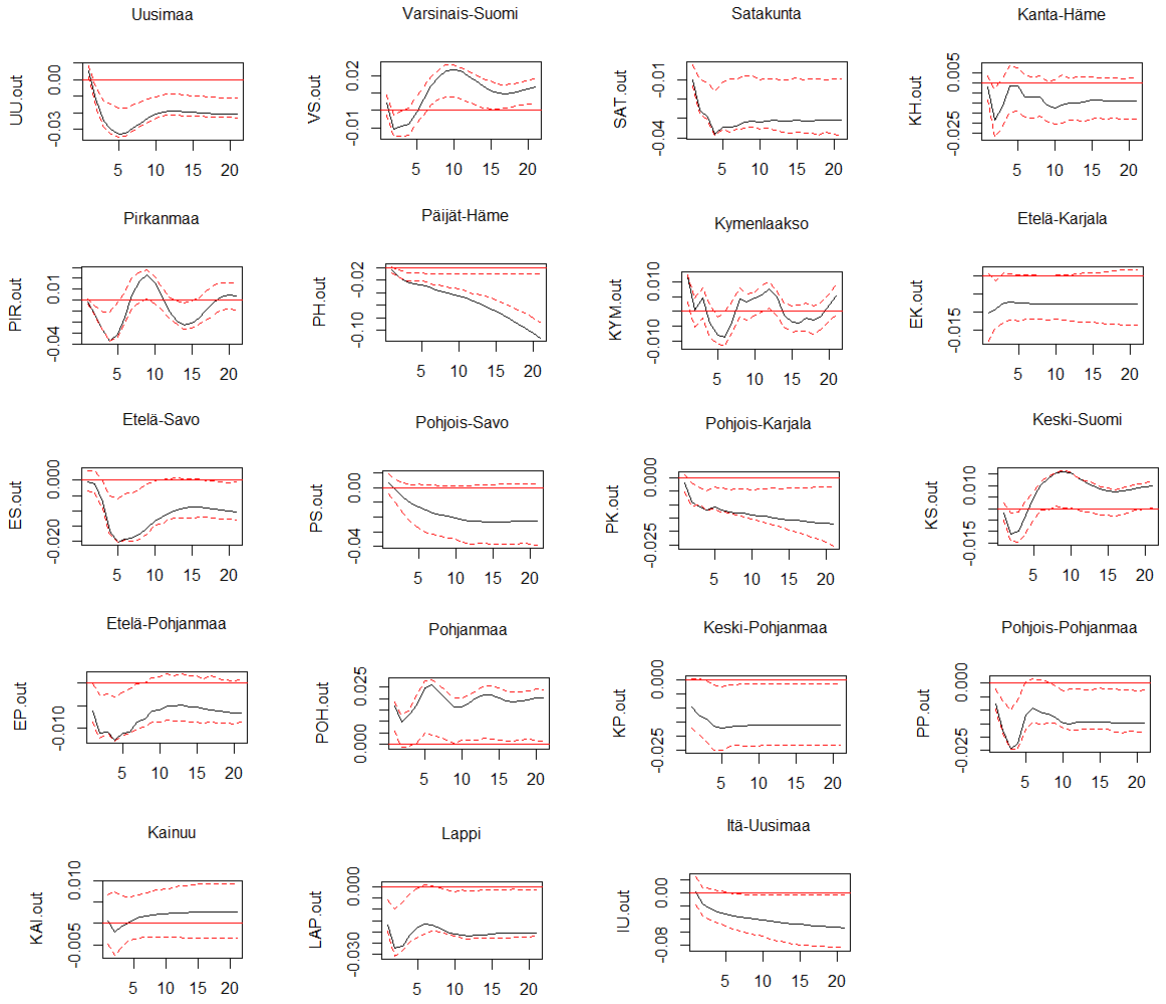

Figure 5: Output responses to a shock to g^{eff}

be long enough. One should still keep in mind that the long-run elasticities presented in Table 13 include all feedback effects. Thus the elasticities are uncomparable to their structural counterparts (i.e. elasticities from production function studies). In Table 13 I have marked elasticities for those variables for which the whole response horizon is significant with an asterisk. Only a small minority of response horizons is classified as significant. Moreover, the regional elasticities are now calculated with respect to both transport infrastructure located inside the region g^{in} as well as the effective transport infrastructure g^{eff}.

If the left columns, or the long-run elasticities with respect g^{in} are inspected first on their own, overall the qualitative result from previous studies that smaller geographic scale produces lower elasticities seems adequate. Some exceptions to this rule are present in Table 13 but on average the result holds that national level elasticities are larger (and for most regions the sign

of elasticity is the same). Moreover, the elasticities with respect to g^{eff} are in general larger than their g^{in} counterparts but the responses are still for most regions qualitatively the same (that is, negative). This seems intuitive since g^{eff} consists of within-region and outside-region transport infrastructure capital stocks and therefore the dynamics between variables are likely to be similar than in the system that includes only g^{in}. Also it makes sense that introducing one unit shock to series with larger values in absolute terms $\left(g^{eff} > g^{in}\right)$ is likely to produce larger responses by other variables in the system.

	Long-run elasticity of ... with respect to g^{in} and g^{eff}					
Region	Real GDP		Private capital		Employment	
Finland	-1.64		-0.80		-1.80	
Uusimaa	-2.30*	-2.39*	-2.38*	-2.49	-1.72*	-1.82*
Varsinais-Suomi	1.88	1.89	-1.27	-2.43*	-0.92	-2.92*
Satakunta	-0.74*	-2.56*	0.10	-1.13	-0.91*	-2.63*
Kanta-Häme	-0.50	-2.98	0.51	-2.89	0.31	-1.98
Pirkanmaa	0.37	-1.12	-0.43*	-2.36	0.04	-2.23
Päijät-Häme	-0.26	-2.11	-0.31	-3.76	-0.71	-4.62
Kymenlaakso	-0.13	0.07	-0.21	-1.24	-0.27	-0.81
Etelä-Karjala	-0.94	-1.46	0.14	-1.19	-0.58	-2.25*
Etelä-Savo	-0.24	-1.67	-0.36	-3.08*	-0.36	-1.67*
Pohjois-Savo	-2.26*	-4.64	-2.76*	-4.65	-2.39*	-4.61
Pohjois-Karjala	-2.85	-3.71*	-1.28	-1.71	-2.10	-2.87*
Keski-Suomi	0.03	5.24	-0.10	-1.52	-0.53	-1.96
Etelä-Pohjanmaa	-0.49	-1.07	0.27	-0.73	-0.47	-1.12*
Pohjanmaa	0.01	10.31	-0.05	-5.21	-0.47	-1.87
Keski-Pohjanmaa	0.49	-2.47	-2.33	-0.55	0.08	-2.08
Pohjois-Pohjanmaa	-0.05	2.98!	-0.90	2.13!	-0.53	1.79!
Kainuu	0.07	0.35	-0.76	-1.92	-1.29	-1.95
Lappi	-2.48*	-4.78	-4.16*	-6.41*	-1.39	-4.28
Itä-Uusimaa	-4.20	-2.07	0.41	-0.98	-0.81	-1.31

Note: The long-run elasticities present the long-run percentage change in real GDP (y), private capital (p), and employment (e) per one percent long-run change in transport capital stock (g). The elasticities are obtained by dividing the long-run (N=50) response of y, p, and e to a shock to g, respectively, by the long-run response of g to a shock to g. An asterisk (*) indicates that the 68 % CI does not include value zero. An exclamation mark (!) indicates that the positive long-run elasticity is due to both g^{eff} and $y/p/e$ responses being negative.

Table 13: Long-run effects of transport infrastructure capital

In order to get a better understanding if there exists any significant correlation across regions between the economic impact of transport infrastructure capital and the relative degree of

capital endowment I have drawn Figure 6. On the left in Figure 6 the direct effects versus output to transport infrastructure ratio are presented and on the right, the spillover-included effects versus output to effective transport infrastructure ratio. In theory, regressing output elasticity on output to transport infrastructure ratio should result to upward sloping regression line since it is expected that the output elasticity is stronger on regions that have a relatively low endowment of transport infrastructure. As can be seen from Figure 6, the regression line is only slightly upward sloping in both cases and not much can be said about the relationship.

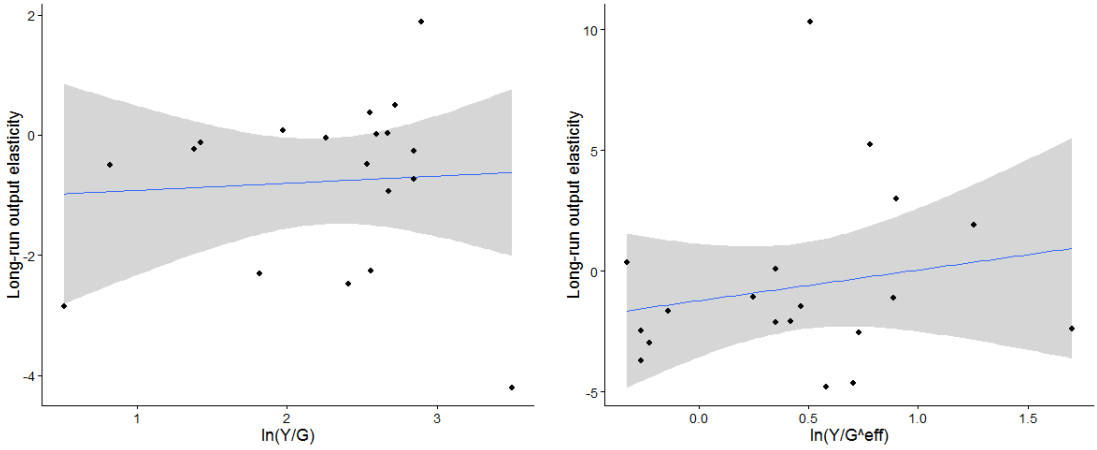

Figure 6: Relationship between regional long-run output elasticity and output to transport infrastructure ratio

5.4 Reverse Causation and Sensitivity Analysis

The issue of reverse causation has been brought up several times in literature (Kamps, 2005; Roca-Sagalés and Sala, 2010). Performing Granger causality tests would be one option to test whether the assumption of variable endogeneity used in this thesis is reasonable or not. However, IRA can also be used for the purpose of examining causality (Lütkepohl, 2001). In particular, it should be interesting to test whether there is feedback from output to transport infrastructure capital. In the context of VAR methodology, this corresponds to investigating whether the impulse responses of transport infrastructure capital to a shock to real GDP are significantly different from zero in the response horizon.

The impulse responses of transport infrastructure capital to an output shock for some of the regions are presented in Figure 7. The cumulative responses are qualitatively different (positive) from a transport infrastructure shock to output, though they cannot be classified as significant. Again I am using the same classification for significance, i.e. considering

responses for which 68 % confidence interval does not include zero as statistically significant. It appears that for all regions transport capital increases moderately after a positive output shock. These results indicate that there is no strong evidence against treating transport capital as an endogenous variable.

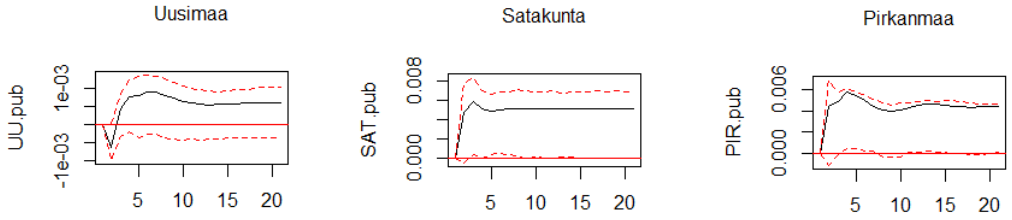

Figure 7: Impulse responses of transport infrastucture variable to a shock to real GDP variable for selected regions

Already earlier it has been mentioned that the IRA may be sensitive to the ordering of the variables in the recursive VAR approach. For a system of four variables there exists $4! = 24$ possible orderings of the variables. Clearly trying all of the orderings is out of question, so I will consider a single alternative ordering. As in Kamps (2005), I place transport infrastructure capital as a last variable. Then the vector of endogenous variables is written as $X_t \equiv [p_t, e_t, y_t, g_t]'$. This is the opposite case of the benchmark case. Now transport infrastructure capital is affected contemporaneously by shocks to all other variables whereas the other variables are unaffected contemporaneously by shocks to transport infrastructure capital. In general, it would be desirable that also the alternative ordering would produce qualitatively similar results compared to the benchmark case. However, Kamps (2005) notes in his study that for Finland (together with New Zealand) the sensitivity analysis produces impulse responses with switching signs.

IRF results show that the alternative ordering does not affect greatly on long-run elasticity signs in national level model. As one can see from Figure 8, the pattern in impulse responses is fairly similar to that of the benchmark case (Figure 3). So it can be stated that the impulse responses are not highly sensitive to the ordering of the variables.

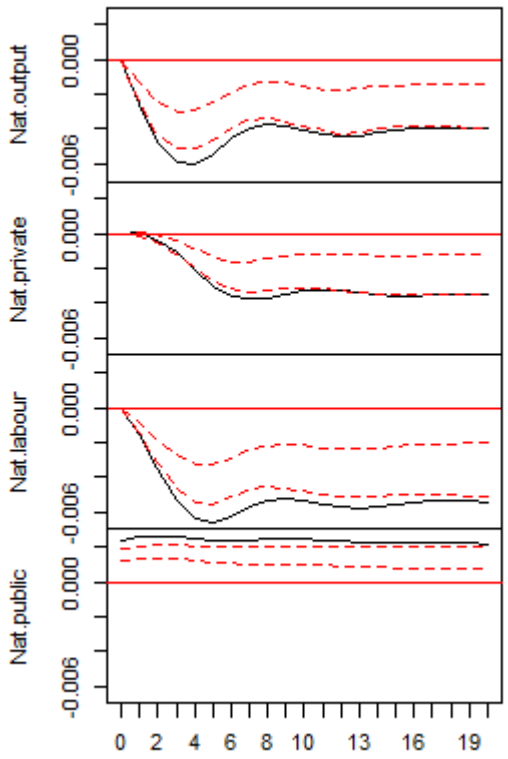

Figure 8: Sensitivity analysis: Alternative ordering impulse responses

6 Conclusions

This thesis aims to examine the dynamic effects of transport infrastructure capital in Finnish regions and in Finland as a whole using the VAR methodology. The national level estimates for long-run effects differ quite a bit from those obtained by Kamps (2005). Whereas Kamps (2005) found evidence of positive long-run effects especially from public capital shock to economic output in Finland, my estimates suggest the opposite. The differences can be explained by several reasons but I will emphasise two of them. First, Kamps (2005) uses total public capital stocks in his study, while I use the transport infrastructure capital stock that forms only fraction of the total public stock. There are no empirical studies for Finnish case using this level of disaggregation in public capital stock that the results could be compared to. Second, the capital stock estimates used arguably have a great impact on final results. Kamps (2005) uses his own estimates (see Kamps, 2004) for government net capital stocks that are not straight counterparts of 'official' (meaning national accounting based) capital stock estimates. The estimates I use for net transport infrastructure capital stocks are, in contrary, based on national and regional accounting data.

Though the signs of long-run effects are contradictory to many previous empirical studies as well as theoretical models, my empirical results support the prediction that national and regional level effects differ from each other. On regional level, it seems that the direct effects are in general lower than the national level long-run elasticities. The pattern of responses is similar for majority of regions: a unit shock to transport infrastructure capital located within the region itself decreases private capital stock, labour and regional output. Hence my results suggest that publicly funded transport infrastructure investments crowd-out private sector variables.

When compared to results of Márquez et al. (2011) and Roca-Sagalés and Sala (2010), the results for Finnish regions are significantly more uniform than for Spanish regions. Still some regional disparities especially in the output responses can be pointed out. A region of Varsinais-Suomi exhibits a strong (yet not significant) positive output response to a shock to transport infrastructure capital. Also for regions of Pirkanmaa, Keski-Suomi, Pohjanmaa, Keski-Pohjanmaa and Kainuu output elasticities are positive with respect to inside-region transport infrastructure capital stock. It should be noted, however, that no clear correlation between relative amount of transport infrastructure capital and output elasticity seem to exist.

Attempts for tracing out spillover effects did not result anything significant. Some conclusions can be made, however. It seems that direct effects of transport infrastructure investment are relatively more important in geographically central regions such as Uusimaa. On contrary,

spillover effects are relatively more intense in the peripheral regions. In general the spillover effects also seem to be negative, meaning that changes in transport infrastructure capital stock in close-by (not necessarily geographically close-by) regions reinforces the direct effects. Chosen method for the estimation of the outside-region transport infrastructure capital reputedly plays a crucial role in detecting spillover effects. Using trade matrix as a weight matrix has many advantanges compared to weight matrices based on geographical distances but this approach also includes some caveats. Namely, it makes no differentiation on how geographically close is the stock of external transport infrastructure capital with respect to the particular region that the outside-region capital stock is estimated for. This assumption is plausible for a small country that has no isolated regions (as argued by Roca-Sagalés and Sala, 2010) but for Finnish case some combination of trade volume and geographic distance as a weight matrix should be at least examined in order to enhance the analysis of spillover effects.

One of the most distinctive features of IRFs presented in Section 5 is that the cumulative response of transport infrastructure variable to a shock to itself is positive in almost every model, whereas for the private capital, labour and output variables the cumulative responses were in most cases negative. Based on an assumption that neoclassical production function is a valid representative of relationship between variables, this kind of behaviour implies that the transport infrastructure to output ratio is beyond its optimal level. However, one possible explanation to this rather unconventional pattern of responses could be that the recession of 1990s should be considered more carefully in analysis. Using a structural model instead of unrestricted one could hence improve quality of results or even change the pattern of responses and, consequently, the signs of long-run elasticities.

One possible way to extend the current analysis would be to examine if spatial dependence exists among long-run regional effects. Márguez et al. (2011) found a strong geographic pattern for long-run regional effects from public capital on private capital. Furthermore, they made a conclusion that Spanish regions can be divided into two spatial clusters of rich and poor regions. Including spatial dimension into analysis would enable looking for corresponding patterns also for Finnish regions.

In addition, it would be interesting to study if using the total public capital stock as a variable would produce similar results, or are public investments on transport infrastructure particularly ineffective. Bearing in mind that many authors have argued that the core infrastructure of streets and highways should be the most effective group of fixed public capital, the crowding-out effects could be even stronger for the total public capital stock. Also using disaggregated sectoral data for output in analysis would deepen the understanding of transport infrastructure capital effects. Most likely transport-intensive sectors should benefit from transport infrastruc-

ture investments more than other sectors. In that case investments in transport infrastructure might influence the production structure of a particular region. Moreover, more extensive research on optimum location of transport infrastructure investment is crucial in order to identify in which regions further investments would have a greater impact, as suggested for example by Roca-Sagalés and Sala (2010).

Public investments have been long considered as a key determinant of the macroeconomic performance at a regional level (Munnell, 1990; Márguez et al., 2011), and hence productivity of different types of public capital most likely remains as an important research problem also in the future. Concentrating only on the direct effects might give biased results especially with a variable like transport infrastructure capital since regions are increasingly interrelated. Thus including spillover effects in the evaluations is required for a comprehensive assessment of the total economic impact of transport infrastructure investment.

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Part I

Appendix

Table 14: Individual ADF-tests for regional data

Region	y	Δy	e	Δe	p	Δp	g	Δg
Uusimaa	-2.58	-2.72*	-2.91	-2.72*	-2.30	-1.97	-1.15	-3.86**
Varsinais-Suomi	-2.86	-3.33**	-2.87	-2.96**	-1.99	-3.49**	-3.37	-4.14**
Satakunta	-1.55	-4.04**	-2.16	-3.28**	-3.24	-3.02**	-1.74	-3.37**
Kanta-Häme	-2.74	-4.42**	-2.04	-3.06**	-2.77	-2.21	0.04	-0.59
Pirkanmaa	-1.45	-3.97**	-1.73	-2.89*	-2.51	-2.60*	-1.53	-4.75**
Päijät-Häme	-2.06	-4.08**	-2.24	-2.89*	-2.48	-1.26	0.23	-2.61*
Kymenlaakso	-2.87	-5.03**	-2.69	-2.84*	-2.71	-3.32**	-2.53	-2.47
Etelä-Karjala	-2.63	-4.50**	-2.28	-2.87*	-1.79	-4.22**	-1.21	-3.74**
Etelä-Savo	-2.74	-2.91*	-2.76	-2.26	-3.24	-1.70	-1.15	-1.89
Pohjois-Savo	-2.97	-3.32**	-2.97	-2.45	-2.24	-2.23	-2.33	-4.43**
Pohjois-Karjala	-1.89	-3.80**	-2.60	-2.15	-2.23	-4.93**	0.21	-0.29
Keski-Suomi	-2.95	-4.45**	-2.60	-3.00**	-2.21	-3.44**	-1.18	-3.55**
Etelä-Pohjanmaa	-1.89	-3.07**	-2.54	-2.42	-2.93	-2.06	-0.33	-2.65*
Pohjanmaa	-2.38	-3.81	-2.88	-2.89*	-1.24	-3.88**	-0.45	-2.93**
Keski-Pohjanmaa	-1.85	-3.84**	-2.23	-2.45	-3.40	-2.97**	-1.63	-3.66**
Pohjois-Pohjanmaa	-1.31	-3.70**	-2.32	-2.88*	-3.95	-4.00**	-2.14	-3.14**
Kainuu	-3.22	-4.22**	-2.26	-2.52	-1.88	-3.58**	-1.21	-3.38**
Lappi	-2.28	-4.61**	-2.58	-2.51	-1.39	-2.64*	-2.47	-4.00**
Itä-Uusimaa	-1.72	-3.47**	-3.31	-2.74*	-1.56	-5.37**	-1.43	-3.89**

Note: An asterisk (*) indicates that the test is rejected at the 10 % significance level. A double asterisk (**) indicates rejection at the 5 % significance level. The critical values for those significance levels (for Δ-series) are -2.60 and -2.93, respectively.