Copenhagen Business School
Frederiksberg, 15 May 2019

International House Price Convergence

Housing dynamics in a globalist perspective

Master's Thesis

Author: Lennart Gregor Janssen

Supervisor: Natalia Khorunzhina

M.Sc. Advanced Economics and Finance (cand.oecon.)

Department of Economics

Pages: 72

Characters: 134,482

Student Number: S115719

Abstract

The aim of this study is to examine convergence behaviour of housing prices and underlying common factors for an international sample of cities. The framework is derived from a spatial utility equilibrium model. A novel regression-based convergence test is used to detect house price convergence. The overall sample shows divergence, while convergence is found for subgroups of cities. In relation to the model framework, the results of a logistic regression suggest that GDP per capita growth and population growth have a significantly positive influence on convergence club membership and consequently on the house price convergence level. Derived policy recommendations suggest that in light of increasing wealth inequality, measures must be taken to ensure that housing keeps being affordable for everyone. Furthermore, high housing supply elasticity must be ensured so that cities are flexible to respond to rapid increases of urban population.

Keywords – House Price Convergence, Club Convergence, Spatial Utility Equilibrium, Multinomial Logistic Regression

Author Contact Information – Lennart Janssen, lennart.janssen@live.com

Contents

List of Figures

List of Tables

1 Introduction

The long-run increase of housing prices in developed countries (OECD, 2019) as well as the recent global financial crisis that had its origin in a turmoil of housing markets in 2007 led to an increased interest in understanding the housing market among researchers worldwide. On a microeconomic level, housing decisions have a crucial impact on the individual household portfolio (Flavin and Yamashita, 1998). Hence, the dynamics of housing prices are prone to have a major influence on peoples livelihoods and, by extension, the overall economy. For instance, increasing housing prices in a city tend to crowd out low-income households (Gyourko et al., 2013), which makes employment less accessible for this group (Kelly et al., 2013) and therefore affects the economy of the city. Furthermore, house prices have a major impact on the distribution of economic wealth and are of major importance in explaining household saving and consumption (Englund and Ioannides, 1997).
Amidst the popular impression that housing in attractive cities of developed countries becomes increasingly unaffordable for many people, these facts are prone to spark increased interest in the topic of housing price dynamics. Consequently, this topic received an extended amount of attention from researchers in recent times. The dynamics of housing prices in cities are of interest not just for urban planners and decision-makers, but also for the average individual that decides to live in them. Housing is an elemental ingredient of individual well-being and at the heart of peoples lives.

Furthermore, since the beginning of the 20^{th} century, increasing industrialisation and globalisation across the world led to a rapid increase in the share of the world population that live in urban areas (Klein Goldewijk et al., 2011), being currently at just over 50% (UN, 2018). The future outlook points at the same direction: by 2050, over two third of the world population is expected to live in urban areas, with only very few countries expected to have more people living in rural areas than in urban ones (UN, 2018). Consequently, a comparably larger amount of the world population is influenced by how house prices in urban areas develop over time.

So far, researchers only examined this topic either for cities or regions within a country (e.g. Cook (2003); Clark and Coggin (2009a); Hiebert and Roma (2010); Apergis and Payne (2012)) or for countries as a whole (e.g. Englund and Ioannides (1997); Demir and Yildrim (2017); Tsai

(2018)). In an increasingly globalised world, it is of importance to extend these approaches to a sample that consists of cities in multiple countries. Global rapidly increasing urbanisation demands solutions for challenges that come with it, and an international perspective provides the best foundation to compare house price development patterns and their fundamental factors globally. Additionally, it can be a foundation for transferring best-practices of solutions to challenges that urbanisation and increasing housing prices bring.

The idea is to detect long-run relationships by testing for convergence in house prices across a globally oriented sample of cities. The application of a new convergence test invented by Phillips and Sul (2007) makes it possible to find international subgroups of cities that converge to different levels of housing prices over time. These different subgroups of housing price convergence are called convergence clubs. The categorisation of cities in subgroups makes an excellent foundation for testing the Rosen-Roback framework, also called the spatial utility equilibrium theory (Rosen, 1979; Roback, 1982). According to the theory, the price of housing is one of multiple factors that affects the utility of individuals. In a spatial utility equilibrium, all individuals must have the same utility across space, which suggests that housing prices are related to other fundamental factors that influence utility. Consequently, fundamental factors can be an indicator for housing price dynamics. The hypothesis is tested by the application of a logistic regression. This study develops a pioneering approach that relates the house price convergence method directly to a spatial utility model. Furthermore, applying the framework and the methodology to a multinational sample is a novelty. By pursuing this approach, the following questions will be answered:

Does a global conversion system of housing prices exist?

Is there evidence for international alignment in fundamental factors of house price dynamics?

Answering this questions delivers valuable insights into the globalisation of house price developments. The gained knowledge opens up and expands opportunities for sharing policy practices across administrations to tackle challenges that increased urbanisation comprises. Furthermore, it is a base framework that can be used for extended research on data that becomes available in the future.

Chapter 2 gives an overview of past housing price research. After an elaboration on the different equilibrium approaches in housing economics, the focus shifts to past research on long-run relationships of housing prices and housing price convergence.

In Chapter 3, the theoretical framework explains the roots and development of the spatial utility equilibrium theorem to a measure of house prices. The model is then modified to fit the methodology as well as the research purpose.

The data itself is presented in Chapter 4. Additionally to data descriptions, the chapter elaborates on the history of cities in general and in context with the sample countries. Furthermore, reasons and justifications for the choice of countries that are part of the sample of house price indices are presented. Lastly, a detailed description of the fundamental data follows.

Chapter 5 describes the methodology used to examine the research questions. The convergence algorithm of Phillips and Sul (2007) is explained in detail. Additionally, the logistic regression model is presented. It is used to find alignments between the behaviour of the fundamental data and differences in the dynamics of house price developments across the sample, which are expressed as the membership of cities different house price convergence clubs. The main focus here is set on the general theoretical background, obtaining regression coefficients, and the derivation of marginal effects, as these are used in the analysis.

The results obtained in the analysis are interpreted in chapter 6. The outcomes are discussed in light of the spatial utility equilibrium theory. Based on the resulting implications, policy recommendations are developed.

Lastly, chapter 7 outlines general conclusions, limitations, and ideas for further research on the topic.

2 Literature Review

The first section of the literature review is focused on housing price equilibrium approaches, which investigate the theoretical foundation of housing prices. Fundamentally, there are two different equilibrium approaches. The first one assumes housing to be a financial asset like any other. There is a differentiation among researchers, with one side investigating the equilibrium condition or indifference between renting and owning a home, and the other side examining the efficiency of housing as a general financial asset with a focus on investigating housing market efficiency. The second approach is the spatial utility equilibrium theory. It sees housing and housing prices as part of a utility framework for individuals, firms, and homeowners.
The second section gives an overview of past work on the topic of long-run relationships and convergence of housing prices.

2.1 Equilibrium Approaches

Regarding the first approach, Poterba (1984) introduces an asset-market model that states that there should be an equilibrium between renting and owning a home. He analyses the impact of the expected inflation rate and tax deductions on housing prices and the equilibrium size of the housing stock. An application is done by Muellbauer and Murphy (1997), who develop a housing price model based on inverted demand equations – which include user cost, population, real interest rate, and supply of housing, among other fundamental variables. In Case and Shiller (1987), the authors test whether the market for single family homes is efficient. This approach is further extended in Case and Shiller (1989) and related works of the same authors. Essentially, the papers rely on an approach where a home is seen as a pure financial asset. An individual then has to make the decision whether to purchase a home now or next year, in light of earning risk-adjusted returns from investing in housing versus other assets.
The financial asset approach becomes more apparent in the empirical work of the papers mentioned. Combined with the findings from Poterba (1984), Case and Shiller (1989) attempt to find a measure of real return on housing for metropolitan statistical areas (MSAs) in the United States (US). The model is extended by incorporating taxes, housing prices, and interest rates to

calculate the theoretical rent for the home. The house price is then calculated with a dividend discount model; a home price is equal to the sum of discounted rents in the future. In Case and Shiller (1990), the authors extend the model again to explore the forecastability of housing prices and excess returns on investment in owner occupied housing. They construct excess returns by using, additionally to rent and price indices, mortgage rates, tax rates, treasury bill rates, and expenditures on maintenance and repairs, honouring recommendations by Poterba (1984) with the latter. They find weak serial correlation for housing prices in four US-cities, with positive serial correlation for shorter time horizons and negative serial correlation for longer time horizons. They conclude that excess returns in the housing market relative to debt exist. Moreover, they observe the forecasting power of multiple independent variables for housing prices. They find that the ratio of construction costs to housing prices, the real per capita income growth, and increases in the adult population in one year have a significantly positive relationship to price changes and excess returns in the subsequent year. In both papers, the conclusion is that the housing market is inefficient according to the theory. In later years, multiple research papers take the model further. Abraham and Hendershott (1996) explicitly state that the findings from Case and Shiller (1989) and Case and Shiller (1990) about the lagged appreciation rate in price regressions being positive is an obvious hint to a bubble. As a consequence, Abraham and Hendershott (1996) aim to find a proxy for the bursting tendency of bubbles and detect that real housing price appreciation is affected by construction cost, income changes, and the real after-tax interest rate in a major subset of their data.

Malpezzi (1999) investigates the inefficiency argument with an Error Correction Model, estimating an equilibrium housing price-to-income ratio for a sample of MSAs in the US, with the conclusion that housing price changes are correcting towards an equilibrium in the long term and are therefore efficient as well as partly forecastable. Gyourko and Voith (1992) analyse time series data of US MSAs. They find suggestive results for equal appreciation in housing prices among different local areas and find positive serial correlation for a few. Jud and Winkler (2002) obtain similar results. They show that housing price appreciation rates vary due to location-specific fixed effects. Their extended focus is set on variables influencing supply, namely land availability limitations and the local policy landscape. Capozza et al. (2004) investigate a dataset for MSAs as well and find that housing prices react differently to overall economic shocks and differences in serial correlation parameters, depending on local differences in expectations, supply costs, and information costs.

Using the argument that both the rent-own equilibrium condition and the financial asset equilibrium condition have the key prediction of absence of excess returns of owning, Glaeser and Gyourko (2007) claim that one can conflate both approaches. Furthermore, they criticise the empirical validity of each approach, arguing that rented and owned units have different attributes and renters and owners are different types of occupants. More specifically, they find that housing characteristics and locations for each type are quite varying. Additionally, renters and owners show differences in income, volatility of income, and family structure. The conclude that the "housing price and rent series can be understood as the cost of two different types of housing, reflecting different demands for two related, but not directly comparable, markets." Related to that topic, Mikhed and Zemčík (2009) test for causality in both directions using US MSAs and find only causality in first differences in the direction from rents to prices. However, they note that this connection breaks down in the presence of a housing bubble.

The second approach, the spatial utility equilibrium theory, is a key attribute of past and modern urban economics. At the core, the theory implies that wages, population, housing prices, and other amenities comprise the utility of an individual who is living in a city. Overall, an utility equilibrium must hold across all cities, so that individuals are indifferent about where they are located. Glaeser et al. (2006) specify this statement for housing prices: "housing prices reflect the willingness to pay for one location versus another."

The primary model for inter-city analysis in regards to this model is based on contributions from Rosen (1979) and Roback (1982), who pioneered in research relating utility equilibria of individuals who live in cities. Rosen (1979) examines city-specific relations between wage and amenities. Roback (1982) extends the model by looking at inter-city price dynamics and including the utility of the firm. More importantly, she includes potentially omitted variables into the model, for instance further amenities, which are city-specific and may differ from city to city. City-specific amenities, she argues, are decisive for differences in housing prices. In application, the proposed model suggests that wages as well as housing prices will adjust so that the marginal resident of each city will receive an identical utility.

Zabel (2004) uses the theory to build different versions of equations for housing demand and tests housing demand elasticity for each of them with a sample of US MSAs. Glaeser et al. (2006)

do empirical work on a self-made extension of the Rosen-Roback framework that examines the interrelation of population, per capita income, and housing prices. They stress the importance of including housing demand and supply into the overall utility framework. Saiz (2010) uses satellite-generated data of U.S MSAs to estimate developable land availability and include it into the utility framework as a housing supply elasticity measure. He finds that a geographical constraint leads to higher housing prices as well as more housing regulation.

2.2 Long-Run Relationships and Convergence

Research of long-run relationships of housing prices as well as housing price convergence gained traction later than the research on housing price equilibria described in the last section. This is most likely due to the fact that methods in time series econometrics, which are heavily used in this kind of research, experienced leaps of development in recent times.

A considerable amount of research in this area is concerned with the "ripple effect", which states that housing price changes observed in a specific region eventually spread to other regions. MacDonald and Taylor (1993) apply a vector autoregression (VAR) model and derive impulse response functions to estimate the ripple effect of Greater London on other regions in the United Kingdom and discover the presence of a ripple effect, although clearly stating that they did not attempt to investigate the underlying reasons. Meen (1999) fills that gap by providing theoretical explanations and an empirical application focussed on spatial coefficient heterogeneity. He applies the augmented Dickey-Fuller (ADF) test to the ratio of housing prices in the South East relative to the North of the UK. He is not able to provide evidence that there is a long-run constancy of the ratio of regional housing prices to the national average in the UK. Cook (2003) and Cook (2005) extend the model by applying an asymmetric test of the same kind, finding considerable convergence of housing prices and evidence for the ripple effect. Further applications of the ADF-method can be found in Holmes (2007) and Holmes and Grimes (2008).

For the United States, Clark and Coggin (2009b) apply a "smooth trend plus cycle"-model and unit root tests, essentially applying the method of Meen (1999). They find mixed evidence for convergence of regional housing prices relative to the national average. A more specified research is offered by Gupta et al. (2010), who use first an ADF-test, followed by out-of-sample forecast to find relations between housing prices in Los Angeles, Las Vegas, and Phoenix.

While international comparisons of housing price dynamics on country level are common, there is a scarcity of this research on an international sample of cities. The only exception is Meen (2002), who compares housing prices as well as fundamental variables of the UK and the US on national as well as subnational levels. He finds a long-run relationship between the two housing markets in terms of home prices and underlying fundamentals like real income, wealth, housing stock, and real interest rate.

A very recent approach for analysing housing price dynamics is a clustering algorithm created by Phillips and Sul (2007). Despite other uses, the clustering algorithm is able to find long-run relationships of housing prices in a heterogeneous panel. Furthermore, it is able to detect subgroups of the panel that converge to a similar price level over time, which is a novelty. A closer explanation is given in the methodology.
Apergis and Payne (2012) apply the method on US states and find three convergence clubs, not doing further research into possible underlying explanations. Kim and Rous (2012) apply the algorithm on US state and metropolitan area panels and examine the general characteristics. Additionally, they use a multinomial logistic regression approach to analyse common factors of the convergence clubs. They find four subgroups of metropolitan areas that show convergence in housing prices and find that housing supply regulation as well as climate are convergence club membership determinants. Apergis et al. (2015) investigate the South-African housing market, finding multiple convergence clubs and give intuitive explanations for underlying causes. Blanco et al. (2016) apply the method on Spanish regions and find multiple convergence clubs. They apply an ordered logit model to find underlying reasons for club membership and find that provinces with larger population growth are more likely to belong to a club with a higher housing price convergence level. Furthermore, they find that geographical proximity as well as initial housing supply play a role in determining club membership. Holmes et al. (2019) investigate local authorities of the United Kingdom in the same manner. They find that, among other variables, income differentials play a crucial role in convergence development. Awaworyi Churchill et al. (2018) examine convergence patterns in Australian state capitals, finding convergence in two subgroups. Tsai (2018) uses the method in her comparison of Eurozone and non-Eurozone

countries regarding convergence in housing prices. She finds that after introduction of the Euro, housing prices of various countries converged towards each other.

Overall, a substantial body of research is concerned with housing prices. It is very apparent that a vast share of it is focused on the United Kingdom as well as the United States. While research for other countries is available, the leaps forward in research techniques have mostly been done with sample data retrieved from the United Kingdom or the United States, which points at the issue of data availability. Furthermore, it is apparent that virtually all papers are focusing either on regions or cities in one country only at a time, or multiple countries on a national level.

This thesis extends the traditional samples by including metropolitan areas of two countries in the sample, which is a perspective that has been left out in the literature so far. Additionally, the study at hand is filling the gap of internationalised research by providing an analysis of the nature housing price dynamics in cities of an international sample. The theoretical framework that is proposed in the next chapter is the first one that directly relates the methodology used in this study to the spatial utility equilibrium theory.

3 Theoretical Framework

As explained in the introduction, the aim of this study is to examine common fundamental factors that cause convergence of housing price developments in cities with a global focus. As a theoretical foundation, an adjusted version of the spatial utility equilibrium model is used to represent the components of housing prices. As explained in more detail below, a spatial utility equilibrium states that the utility of individuals must be equal across all locations.

Before diving into mathematical specifications, an artificial example explains the spatial utility equilibrium concept. Consider a country with two regions, A and B. Both regions provide the same utility to individuals who reside in it. Cities in Region A have decent weather, clean air, and a high wage environment - but also high housing prices. On the other hand, region B suffers from high air pollution and acid rain, caused by a high industry presence. While workers in region B receive high wages as well, housing prices are low as the overall living environment is quite unfavourable due to the disamenities.
Essentially, people living in region B receive a compensation for the worse performance in city amenities by paying less for housing, while earning similar wages to people in cities in Region A. The result of this is that people in both regions receive the same utility. Due to the prevailing conditions, housing prices in both regions are not likely to converge into a common sphere, which implies that differences in housing prices compensate for differences in other characteristics of a city. Otherwise, citizens would move to a city that promises a higher overall utility. Therefore, differences in housing prices are prone to be an indicator for other characteristics of a city, which is what this study examines on an international scale.

The model used in this study is closely related to the spatial utility equilibrium theory. As the point of interest are housing prices, the classic model is used as a foundation to derive an equation for housing prices that is based on a supply-demand equilibrium. The model is an altered version of a housing price approach that was predominantly developed in papers written by the authors Edward L. Glaeser and Joseph Gyurko. The roots of their approach can be found in the spatial equilibrium model approach of Rosen (1979) and Roback (1982). Rosen introduced an equilibrium model that focuses on the behaviour of households as consumers of goods, amenities, and land cost in relation to wages. Roback extended the model by including the behaviour of firms and determined the value of amenities of a city. Admittedly, the main purpose of the Rosen-Roback framework is to develop an index of quality of life in different locations. Nevertheless, due to the fact that land cost is already part of the classic model, there was a possibility to alter the framework to model the price of housing in a city by examining wages, amenities, and other city-specific factors in relation to the equilibrium utility across cities.

This is what Edward Glaeser and Joseph Gyurko did in collaboration with multiple other authors. Their housing cost model is initially described in Glaeser and Gyourko (2007) and further improved as well as regressed in multiple other papers, with the most recent version of it to be found in Glaeser et al. (2014). The authors construct an extended spatial utility equilibrium approach for housing prices to prove the theoretical consistency of some empirical facts of housing market research. While this is not the aim of this study, the model is the most modern approach of the Rosen-Roback framework in regards to housing prices and is used as a base for constructing an estimation model for this study.

The theoretical hypothesis of this study is that if subgroups of cities converge to different levels of housing prices, other utility-generating variables potentially show correspondingly aligning behaviour and can be used as indicators for housing price levels. Therefore, the aim is to test whether certain behaviour in other variables that are part of the utility framework increase or decrease the probability of having a certain house price convergence level.

3.1 Spatial Utility Equilibrium Model

The equilibrium model used in this study is an altered version of the one constructed by Glaeser et al. (2014). It consists of two basic elements, housing supply and housing demand. Housing supply means that in equilibrium, the expected price of housing equals the cost that home builders face when constructing new housing. Housing demand is based on an utility equilibrium condition, which states that consumers must be indifferent about location in cities across space. In other words, every location must provide the same marginal utility.

3.1.1 Housing Supply

The housing supply is represented by home builders, which are risk-neutral and operate in a competitive market. The cost of constructing a house at time t is given by

$$C + c_1 I_t + c_2 N_t \; , \tag{3.1}$$

where C is a static house price, I_t is the amount of construction and N_t represents the population at time t.
As building housing takes time, It is assumed that constructed housing cannot be sold until $t + 1$. The housing supply equation is then:

$$E(H_{t+1}) = C + c_1 I_t + c_2 N_t \; . \tag{3.2}$$

3.1.2 Housing Demand

On the housing demand side, consumers are required to be indifferent across all concerned areas. This requires that utility is equal for all individuals in all locations across space, so that the system is in an equilibrium state. The basic consumer utility function is

$$U = W_t + A_t \; , \tag{3.3}$$

where U describes the utility. W_t describes the value of wages for individuals in a specific city and A_t is the value of various amenities and disamenities the individual in a specific city consumes. Individuals are homogeneous.

Individuals are risk-neutral and can borrow and lend at an interest rate r. The indirect utility of an individual is therefore

$$U_t = W_t + A_t - \left(H_t - \frac{E(H_{t+1})}{1 + r} \right) . \tag{3.4}$$

The indirect utility of a location is therefore dependent on the city-specific variables wage W_t, amenities A_t, and the expected house price increase at $t + 1$.

The next step is to create an equation that relates the utility-altering variables to housing demand. In this way, a full spatial utility model incorporating house prices can be created. To achieve that, an arbitrary neutral city with fully elastic housing supply is taken. Analogue to the housing supply equation, the neutral city has the condition

$$c_1 = c_2 = 0\,, \tag{3.5}$$

so that housing prices in that location are always equal to C. This neutral city supplies reservation utility $\bar{U}$ to a consumer that is located in the city. The reservation utility is equal to $\bar{U} = \bar{W}_t + \bar{A}_t$. The annual cost of living is equal to the difference between the price of the house at time t and the discounted value of the house at time t+1. The mathematical expression for this is $C - \frac{C}{1+r} = \frac{rC}{1+r}$. Then the reservation utility for all cities is equal to

$$U_t = \bar{U} - \frac{rC}{1+r}\,. \tag{3.6}$$

This equation describes the reservation utility of all cities with the neutral value of wages and amenities a t. If equation 3.4 and equation 3.6 are merged, the following equation is created:

$$W_t + A_t - \bar{U} = H_t - \frac{E(H_{t+1})}{1+r} - \frac{rC}{1+r}\,. \tag{3.7}$$

Equation 3.7 illustrates the demand dynamics of housing prices in an understandable manner. The left hand side of the equation expresses differences in wages and amenities of a specific city compared to the neutral city. These differences must equal the housing price minus construction cost and the cost of living. This means that an increase in wages or amenities must be accompanied by either higher housing prices or higher costs of living.

3.1.3 Equilibrium Model

Setting the housing supply equation 3.2 equal to the housing demand equation 3.7 constructs a housing price equilibrium. The merged equation equals the following:

$$H_t - \frac{(C + c_1 I_t + c_2 N_t)}{1+r} - \frac{rC}{1+r} = W_t + A_t - \bar{U}\,, \tag{3.8}$$

which can then be rearranged to

$$H_t = (W_t + A_t) - (\bar{W}_t + \bar{A}_t) + \frac{(C + c_1 I_t + c_2 N_t)}{1+r} + \frac{rC}{1+r} \, . \tag{3.9}$$

Equation 3.9 states that a house price at time t in a city consists of the difference between the city-specific wage and amenities and the neutral city's wage and amenities, the expected house price tomorrow and the cost of living.

3.1.4 Model Adjustments

The altered model of Glaeser et al. (2014) is a good representation of a housing price equilibrium and delivers great insights. The expected behavioural reaction of housing prices on changes in wages and amenities is straightforward: an increase in wages as well as an increase in the value of amenities is expected to increase housing prices in a city.
The influence of population and new construction is a bit more complex. As described by Glaeser et al. (2006), the impact that an increase in population has on housing prices is dependent on whether new construction meets the increased need for housing in a city. This implies that the effect of changes in population on housing prices is an indicator for housing supply elasticity in the market. If an increase of population within a city has a significant impact on housing prices, it indicates that housing supply cannot keep up accordingly. This might be, for instance, due to strict housing regulations or limitations in geographical space. If population changes do not have a significant impact on housing prices, housing supply elasticity is likely to be high.
This relation is very helpful for the analysis that follows later. City-specific data on new construction is not readily available for most countries, less so in an aligned way that enables an international comparison. The relation of population and housing prices as an indicator of housing supply elasticity is therefore an excellent solution to still have an indicator of housing supply despite the absence of a direct measure.

As mentioned in the introduction, this study is utilising housing prices over time to find subgroups of cities with housing prices that are likely to converge to a similar level in the future. These so-called convergence clubs are used as a dependent categorical variable in the model instead of housing prices. The explanatory variables in the model are then used to determine

their influence on the membership of a city in a specific convergence club. As for example, a growth in wages might increase the probability that a city is a member of a convergence club with a comparably higher house price convergence level.
As this means that the dependent variable is a dynamic representation of housing prices, the equation 3.9 must be modified to represent this. To achieve that, all variables of the model are altered to represent growth and all constants are removed. The adjusted theoretical model based on the general housing price equilibrium is equal to

$$\dot{H}_t = \beta_1 \dot{W}_t + \beta_2 \dot{A}_t + \beta_3 \dot{N}_{t-1} \, . \tag{3.10}$$

To estimate this model, proxy variables are used to depict the model as realistically as possible. $\dot{W}_t$ denotes growth in wages, which is proxied by growth in GDP per capita. $\dot{A}_t$ is an indicator for growth in the value of amenities, which is represented by growth in the unemployment rate as an indicator for the socio-ecological environment and average rainfall per month as a proxy for climate conditions. The latter is the only variable that is not represented in a dynamic growth version[1] and can be thought of as a correcting factor for the overall quality of life in a city. $\dot{N}_{t-1}$ is equal to lagged population growth, which functions as a housing supply elasticity indicator as described above. $\dot{H}_t$ is represented by the membership of a city in a house price convergence club. It is a categorical variable, where each club has a different level of housing prices that members of the club converge to. The clubs are detected with the converge algorithm of Phillips and Sul (2007) that is described in the methodology chapter. The estimation model is therefore:

$$Club = \beta_1 * GDP\ p\dot{e}r\ capita_t + \beta_2 * unemplo\dot{y}ment\ rate_t + \beta_3 * rain_t + \beta_3 * popul\dot{a}tion_{t-1} \, . \tag{3.11}$$

A positive coefficient of an explanatory variable indicates that an increase is related to membership in a convergence club with a higher house price convergence level. The expectation is GDP per capita growth and population growth have a positive coefficient, as they are expected to have a positive impact on utility that needs to be compensated by higher housing prices. Increasing rainfall is expected to decrease utility and is therefore expected to have a negative coefficient. The same goes for the unemployment rate, as an increase indicates worsening

[1] Average rainfall per month is a climate variable. As data related to climate is at the mercy of very long cycles, a representation as a growth variable does not make sense in the short-run.

socio-economic conditions. The model is estimated in a logistic regression framework.

The model approach promises great insights into the international dynamics of housing prices and common factors that influence them. While the spatial utility equilibrium framework was mentioned in other papers in connection to the topic of house price convergence, this is the first study that directly derives a model that is fit for estimation with the methodology used. As a consequence, the insights that the later following analysis delivers can be directly inferred on the spatial utility equilibrium approach for housing prices. The next chapter provides an elaborated overview of the data used in the model, with an elaborated explanation of the data accumulation process as well as context for the choice of countries that are part of the sample.

4 Data

Every empirical research relies upon appropriate data. Researchers that examine housing prices have a tradition of lamenting the scarcity of it. This study faces an increased difficulty by taking up the challenge to create an appropriate dataset for cities in multiple countries. Many countries publish yearly house price indices that do not go far enough back in time to accumulate enough observations for a viable analysis, or provide multiple sources with inconsistent methodology. Furthermore, a factor that hinders a fruitful international comparison of cities are the differing definitions of geographical boundaries that are applied to collect housing price data. For instance, while Germany provides data of housing price indices for cities, the usable indices correspond to administrative city boundaries. As the metropolitan area of a city often goes beyond the administrative area of it, it is of little sense to use this data for housing price research. The sample country's definitions of metropolitan areas therefore need to be made comparable, as can be seen in more detail in Section 4.3.[2]

The sample at hand is the result of a tedious and exhaustive attempt to find comparable house price indices. The initial restrictions on data search is to examine only countries that are member of the OECD and to use countries from multiple continents. This is supposed to ensure initial comparability, but nevertheless provide a degree of variation that ensures new insights into the international behaviour of the spatial utility equilibrium theory. After extended inquiries, Canada and the English part of the United Kingdom (UK)[3] seemed to be the most comparable countries, given overall structure, development status, and data availability.[4]

[2]For instance, while the main measure for differences in income in one country might be average income per capita, the other country could use disposable income per household. Extrapolating this example on the vast amount of data categories available illustrates the magnitude of the issue.

[3]For reasons of data availability, this study is only be concerned with cities in England, thereby excluding Wales, Scotland, and Northern Ireland from the analysis. Nevertheless, the term "United Kingdom" is used equivalently.

[4]A few examples for countries with extended attention during the data inquiry process are listed here, accompanied by the reasons for exclusion:

New Zealand	HPI only for regions
Australia	HPI only yearly
China	limited reliability
Germany	HPI only yearly and for administrative boundaries
Japan	HPI only for few cities and on regional basis
Netherlands	HPI only for few cities
South Korea	HPI only from 2008

For these reasons, the section on house price indices is quite elaborate, as it is needed to show how Canada and the UK fit together in the sample. The data evaluation process can be thought of as a framework to use for the case that more countries make house price datasets available.

The first section explains the historical occurrence of cities to highlight the significance of global rapid urbanisation in recent times. Furthermore, it has the purpose of emphasising the historical differences as well as commonalities of city development in Canada as well as the UK. Afterwards, a comparison of Canada and the UK on current metrics follows to highlight the validity of their use as sample countries. Then, an extended analysis of the house price indices used in this paper is done. In research, indices are mostly applied without an extended evaluation of the index data, which is why this study makes an effort to explain the foundations of indices in general and only then elaborate on the house price index sample data. The chapter then ends with a description of the fundamental factor data used for the logistic regression model.

4.1 Cities in a Historical Perspective

Until roughly 10000 - 5000 B.C., humans lived as nomads. The primary source of food was hunting animals and gathering plants, maybe some primitive farming. In this living environment, forming permanent settlements, let alone cities, was not feasible. Only the agricultural revolution, were humans started to domesticate animals and refined farming methods for a reliable food supply, made it possible to sustain a comparably higher population in a permanent space. It also freed up human capital for other crafts that were not related to immediate survival, which increased the speed of technological developments and in turn increased the value of having a city in the first place. Furthermore, due to the technological progress and the resulting abundance of goods, permanent settlements and cities grew to be points of trade. The first permanent settlements in the UK adhering to a modern definition of a city appeared at around 1000 A.D..

While more countries were investigated, this is a small excerpt to highlight the issue. A notable exception with extraordinary data are the United States. The US is excluded from the research for the reason that the sheer amount of big cities and metropolitan areas in the country makes the housing price developments hardly comparable to others. A sample with 120 US metropolitan areas and 20 other cities would mitigate the international aspect of the research crucially. Furthermore, taking a sample of 10-20 US cities depicts only a share of around 25% of the population, compared to roughly 50% for the sample countries. Therefore, including a small sample of metropolitan areas of the United States would not represent the country adequately.

Over the centuries, cities played various roles within the socio-economic system. A main reason for their existence was - despite the notion of permanency - their function as centres of trade and supply of goods. This was a natural development, yet necessary at the same time due to increasing population figures within.

During the middle ages, cities in continental Europe often grew to be very autonomous, sometimes being own city states. Relative to continental Europe, the UK was rather rural, with just a few provincial cities and the exception of London. Nevertheless, due to the sheer size of London at that time, the UK had a much higher share of urban population, compared to an average of below 10% elsewhere. Until that point in time, there was no development of urban areas in Canada, which was inhabited by many different kinds of tribes and cultures, most of them living as nomads or semi-permanent settlers. This changed during the era of colonisation in the 16^{th} and 17^{th} century, where merchants and traders from France and the UK first build colonies, which then eventually grew. Consequently, the population of Canada grew in the east first, which is a hint at the fact that nowadays, more than half of all citizens in Canada live in metropolitan corridors located in the east of the country.

In the 19^{th} century, the UK grew to be a pioneer of industrialisation. This resulted in increasing opportunities for citizens within urban and industrial agglomerations. Adding technological improvements that lead to less demand for workers in the agricultural sector, this led to a rapid growth of cities. In the beginning of the industrial revolution, the Canadian colonies of the UK primarily were sources for raw material. Gradually, this changed, first by facilitating the construction of key transport assets like railways, and then an overall industrial transformation.

During the second half of the 19^{th} and all through the 20^{th} century, the world population grew at an unprecedented pace. Combined with rapid improvements in mobility - the invention of the automobile - , this caused many cities to heavily expand. Furthermore, metropolitan areas in advanced economies experienced a transformation in economical composition, with factories shifting to the outskirts and being replaced by service-heavy economies. In recent decades, these developments gradually shifted to a global scale, with advanced economies outsourcing industrial production to less developed countries. Consequently, these countries grew to be only a few steps behind regarding industrial development and continuing to catch up, with the implied urban consequences

In light of further industrialisation in developing countries and technological progress in developed countries, urban population is still growing rapidly. In 2018, 55% of the world's population lived in urban areas, with a projected 68% for the year 2050 (UN, 2018). As a consequence, the nature of housing price dynamics in cities is becoming relevant for an increasingly larger share of the world population. Therefore, while an inspection of house price dynamics in metropolitan areas of two countries might not be representative for the whole globe as of now, it is nevertheless a valuable source of inference for future urban developments worldwide.

4.1.1 Comparing Canada and the United Kingdom

If one looks at a world map, one could become a little uneasy when thinking about a spatial comparison of Canada and the United Kingdom. Canada occupies roughly 40 times as much space as the UK does, yet hosts only about 40 million citizens, compared to 65 million in the UK. Yet on other metrics, both countries are quite comparable. Canada and the UK are quite similar in development status and align on a lot of social metrics.[5] The economy structure differs slightly, with Canada having a comparably bigger share in industry while the UK is relatively more focused on services. Yet, both countries are in the third phase of the classic three-sector model of the economy (Fisher, 1939) and rank very similar on development indices. The countries have a traditionally strong cultural and commercial relationship. This is due to the historical role of Canada being a British territory. Partly owed to this historical connection, the UK is the fourth biggest goods trading partner of Canada and the largest compared to other countries of the European Union. More importantly, the UK is the second-largest service trading partner of Canada.
The situation is a bit different for the UK, which built up strong trade ties to many European Union members and has traditional commercial relationships to other ex-territories as well. Although Canada is therefore not of similar importance in trade as the UK is for Canada, it can be still regarded as an important trading partner.

Overall, it is evident that both countries are commercially, but also culturally linked. The essence of this is that the two sample countries, despite size differences, are inherently comparable in

[5] Unless otherwise mentioned, numbers and statements based on the these numbers in the descriptive sections following are based on data sourced from the statistical offices of the OECD, World Bank, Eurostat, Statistics Canada, and the UK Office for National Statistics, sometimes used as a base for own calculations.

other categories.

4.1.2 Urban Geographics and Sample Cities

Despite economic ties, both countries also align in measures of urbanisation. Both countries have an urban population share of roughly 80%, which can be described as highly urbanised compared to other countries. The urban share is quite high compared to the worldwide average, which is at around 50%, but quite comparable to the OECD-Average, which fluctuates around 80% as well. As therefore a majority share of the population is exposed to house price developments in cities, a sample of metropolitan areas is a credible foundation for the analysis.

Figure 4.1: Map of Sample Metropolitan Areas

An intriguing factor is that Canada as well as the UK have a centralised structure, with a main metropolitan cluster that comprises some bigger share of the population and multiple smaller metropolitan areas.

In Canada, one of the least densely populated countries by pure size, the most densely populated areas are clustered in and around the big cities that are part of the sample. Around half of the population lives in the Quebec-Windsor Corridor (often just called 'The Corridor') located in Southern Ontario and Southern Quebéc in the east of the country. The main metropolitan areas in this region are Toronto - the biggest city in Canada -, Montreal, and Ottawa-Gatineau. The analysis also includes the next two biggest metropolitan areas, Quebéc City and Hamilton. The metropolitan area Kitchener-Waterloo is worth to mention, but not part of the analysis due to data availability issues. Between the Corridor and the Atlantic Ocean, multiple states make up the Atlantic Provinces, of which Halifax is the biggest metropolitan area. The western coasts main metropolitan areas are Vancouver and Victoria, which are located in British Columbia. The third main agglomeration in Canada is the 'Calgary-Edmonton Corridor' located in Alberta, the most western province of the 'Canadian Prairies'. As it says in the name, the main metropolitan areas in this region are Calgary and Edmonton. Lastly, the analysis includes Winnipeg, located in the eastern province of the Canadian Prairies, Saskatchewan.

The vast majority of the population is located in the southern areas of the country. The metropolitan areas that are part of the analysis make up around 55% of the population.

As one of the most densely populated countries in the world, the United Kingdom is on the other side of the spectrum. Nevertheless, albeit the massive difference in size, the UK shows some similarities in the role of its urban agglomerations.

Focusing on England, where all cities from the sample are located, the metropolitan area of London makes up about a quarter of the population. Besides London, there are further metropolitan areas located more northerly. The northernmost is Newcastle. Further down, the metropolitan areas of Manchester, Liverpool, Sheffield, and Leeds make up a combined share of 10% of the overall English population. Between these and London, there is a third major agglomeration to be found, called the West Midlands. With the major city being Birmingham, it accounts for around 4% of the English population. Further sizeable metropolitan areas are Leicester and Nottingham. Applying a broad definition, the Brighton metropolitan area has a considerate size and is included in the analysis, as a representative of the South East region.

All the sample metropolitan areas of the UK combined make up around 50% of the English population and 40% of the whole United Kingdom.

Having an exhaustive impression about the sample countries and the geographical importance of the sample countries, the next two sections explain the housing price sample data as well as the data accumulation process.

4.2 House Price Indices

House price indices show house price development in relation to a defined base period. The illustrative table 4.1 shows how an arbitrary series of house prices is transformed to an index

Table 4.1: House Price Index Calculation

House Price Index (HPI) Example		
Year	*House Price*	HPI
1995 (Base)	$ 350,000	100
1996	$ 380,000	109
1997	$ 370,000	106

measure by calculating the percentage difference of a housing price to the base period. The ideal choice of the base period is influenced by the perspective the researcher wants to take. For instance, if one is interested in the development of the price of an asset in relation to the year 2009, the base period should be 2009.[6]

In the sample of this study, the base period is set to the beginning of the sample, March 1999. This is not an arbitrary decision. Generally, it is recommended to choose the base period of an index within a time that is not economically conspicuous to ensure a opportunity for comparison to a normal economic environment. As an example, an index of housing prices of the United States should not have a base period within the early 2000s, as housing prices grew extraordinary rapidly during that time. The US housing boom made for high spikes in real estate prices from roughly the early 2000s until the beginning of 2007. Aside from the fact that some other housing markets were affected as well, the global financial crisis following upon

[6]Take the Consumer Price Index (CPI) of the United States: choosing 1950 as a base period would lead to an index value of over 1000 today, which makes comparisons between recent years harder.

impacted the overall economy in an extraordinary way. Setting the base period during that time would therefore distort the sample indices of this study by increasing the probability to have a non-representative base period. Another issue is the distance from the base period to the end of the sample; if the distance between the base period and the end of the sample is too short, the index eventually does not have enough room to evolve growth patterns that are distinctive from each other.

A noteworthy factor are differing methodologies used for calculating house price indices, which are elaborately described by statistical offices. The most straightforward method is the usage of average house prices. Usually, the median, mean, or geometric mean is used to calculate average house prices for an index. Case and Shiller (1987) and Poterba et al. (1991) point out that average and median prices fail to adjust for quality variations over time, which causes higher volatility in house prices that the unadjusted index then fails to account for.
Some statistical offices correct for quality variations by using the hedonic adjustment regression method. Specifically, a house price is then a function

$$p_t^n = \beta_0^t + \sum_{k=1}^{k} \beta_k^t x_{nk}^t + \epsilon \,, \tag{4.1}$$

where x_{nk}^t describes different characteristics of a dwelling, as for example the number of bedrooms, existence of a garden, neighbourhood quality, et cetera.

An alternative to the aforementioned average price calculation is the repeated-sales method. First proposed by Bailey et al. (1963), the method uses repeated sales of the same dwelling to construct a price index. Table 4.2 illustrates three properties that were sold at least twice.

Table 4.2: Repeated Sales Calculation

Repeated Sales Method			
Property	*2000*	*2001*	*2002*
A	\$500,000	\$ 600,000	-
B	\$450,000	-	\$ 550,000
C	-	\$ 600,000	\$ 650,000

The missing prices can be extrapolated by calculating the growth rates of sale prices available. Then, the average of the growth rate for all properties can be used to construct a house price

index. Needless to say, only dwellings that were sold at least twice can be a part of the sample. Problems and biases might arise when houses of different quality have very different sample quantities (Gatzlaff and Haurin, 1998). Furthermore, Clapp and Giaccotto (1998) recommend to exclude dwellings with extraordinary holding periods from the research.
Case and Shiller (1989) suspect possible heteroskedasticity and improved the method by correcting for the movement of residuals over time. Since then, the Case-Shiller repeated sales index grew to be a methodological benchmark in housing price research.

While there are more methods available, the two presented are the most frequently used and also the methods of choice for the data sample. The following section describes the house price sample data of this study.

4.3 House Price Sample Data

The Canadian part of the sample consists of monthly house price indices for eleven metropolitan areas.[7] The house price index is published by a data company called Teranet, in collaboration with the National Bank of Canada. It is recognised by the government and used for official statistics.
The United Kingdom part of the sample consists of monthly house price indices for ten metropolitan areas[8], published by the Office for National Statistics (ONS). The sample in this research is closely aligned to the biggest metropolitan areas in England only. All other countries that are part of the United Kingdom[9] are excluded due to a lack of fundamental factor data.

As mentioned above, an important factor in making house price indices for metropolitan areas comparable is the geographical definition of what a metropolitan area actually is. An increasing amount of statisticians and researchers apply advanced methods to redefine the boundaries of metropolitan areas due to the increasing disparity between administrative borders and the real economic and social borders of cities. The Canadian housing price data is aligned with the official definition of a 'census metropolitan area' (CMA). The definition attempts to detect

[7] Calgary, Edmonton, Halifax, Hamilton, Montreal, Ottawa, Quebec, Toronto, Vancouver, Victoria, Winnipeg. Source: Teranet–National Bank House Price Index, Canada.

[8] Birmingham, Brighton, Leeds, Leicester, Liverpool, London, Manchester, Newcastle, Nottingham, Sheffield. Source: Office for National Statistics (ONS)

[9] Wales, Scotland, Northern Ireland

metropolitan areas that show economic, social, and spatial integration. At the heart of the definition is the existence of predefined city cores. Surrounding census subdivisions are then included in the CMA depending on the degree of spatial overlap with the urban core, commuter flows, as well as spatial proximity.[10] The commuter aspect of the rule is quite prescient and is increasingly used in defining borders of metropolitan areas. The approach helps to make a distinction between areas that actually depend on the core of the urban agglomeration versus areas that have a relation to the metropolitan area, but are not strongly economically and socially dependent on the initial metropolitan core. It therefore helps to provide a more realistic picture of an interlinked metropolitan area.

While Canada offers a clear-cut definition for metropolitan areas, the opposite is the case for the United Kingdom. The country has an overwhelming aggregation of different, sometimes overlapping, administrative unit types. There is no sophisticated official definition of a metropolitan area. The closest attempt by the ONS for a definition are the inquiries on 'urban areas' with a 'bricks-and-mortar'-approach. In essence, the definition states that physically connected built-up areas belong to an urban area. Needless to say, this does not come close to a sophisticated definition of an socio-economically integrated metropolitan area.

Luckily, the OECD and European Union jointly developed an approach to define 'functional urban areas' that is closely aligned with the approach taken in Canada (OECD, 2013). It includes, for instance, the commuting approach taken in the Canadian definition. Taking into account the fact that the UK house price index is published only for the lowest possible administrative level in the UK (local authority), there exists an opportunity for implementing the definitions given by the OECD to closely align metropolitan area definitions of the UK and Canada.

By applying OECD-definitions for metropolitan areas, UK house price index sample data is manually constructed. The house price index for each metropolitan area is created by averaging all local authority indices that belong to a metropolitan area according to the OECD-definition, weighted by the population of each local authority.[11] While this process is tedious, it provides

[10] The entry on CMAs in the dictionary of the Canadian 2016 census gives a detailed explanation on the process of defining a CMA. Source: www12.statcan.gc.ca

[11] For instance, The house price index for Manchester does not just include the administrative metropolitan borough, but also five other local authorities that are economically linked to it.

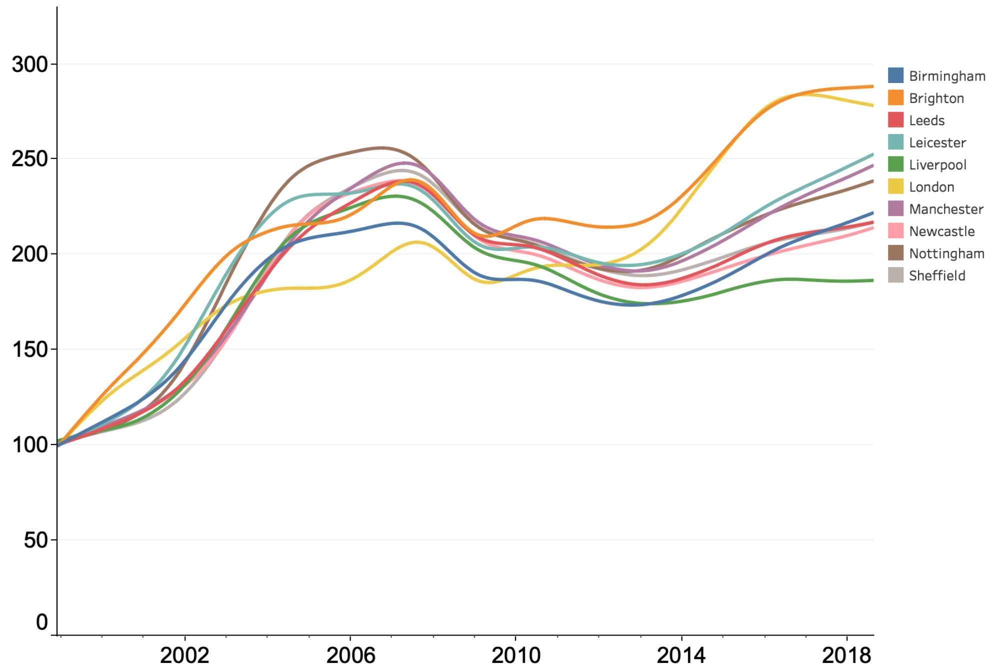
the possibility to create a very precise house price index for metropolitan areas that perfectly aligns with the Canadian definition of metropolitan areas.

For further alignment, the housing type that is part of the index is restricted to single-family homes for both sample countries. The Canadian index is calculated with the repeated-sales method, the UK index with hedonically-adjusted average house prices. The Canadian dataset starts March 1999 and runs until November 2018. While the UK index theoretically starts earlier, the dataset is therefore restricted to this time frame. Furthermore, the house price indices are deflated by using national Consumer Price Indices from the Federal Reserve on a national level. Finally, the natural logarithms of the data are used in the analysis.

Due to the fact that the house price indices have a monthly frequency, it is recommended to use a filter to remove short-term fluctuations and cyclical components. The method of choice is the Hodrick-Prescott Filter, which is used by Apergis and Payne (2012), Blanco et al. (2016), and Awaworyi Churchill et al. (2018), among others, for the same type of research.

Figure 4.2 gives an overview of the real filtered house price indices of the sample metropolitan areas located in the United Kingdom.

Figure 4.2: United Kingdom - Real House Price Index

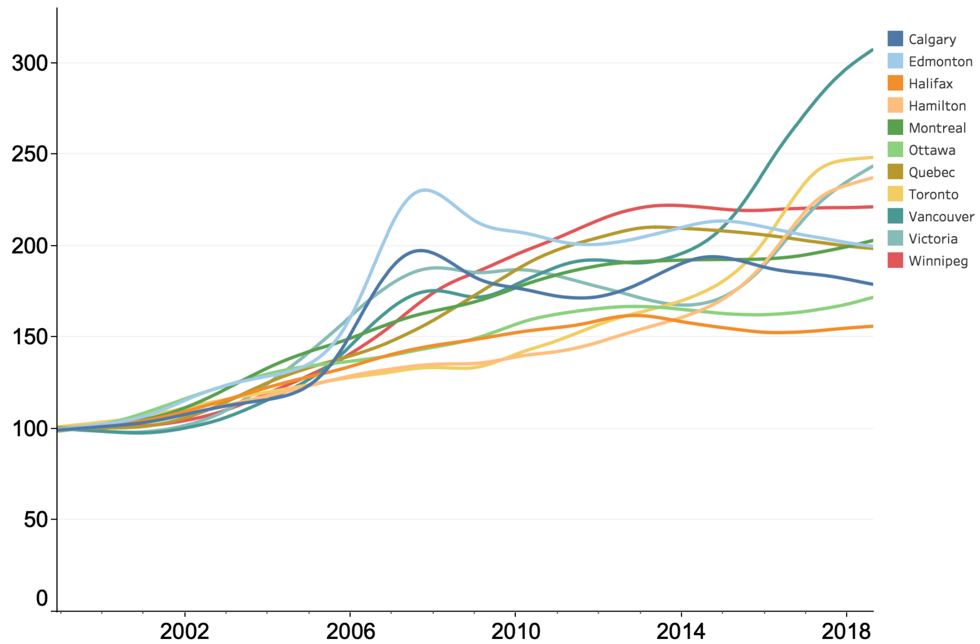


(Base Period: March 1999)

It is clearly visible that the United Kingdom experienced, similar to the United States, a housing boom in the 2000s. According to Wachter (2015), the major reason for this was weakened regulation for some types of mortgage funding, which shows similarities to the issues in the United States at that time. After a downturn until the end of 2014, housing prices slowly started to increase again. The most notable increases can be observed for London and Brighton, while all other cities show less rapid house price growth. The lowest increase since 2014 can be observed for Liverpool.

While the spike in housing prices during the housing boom in the 2000s is very obvious for the UK, figure 4.3 shows a much less pronounced impact on the Canadian part of the sample during that time period.

Figure 4.3: Canada - Real House Price Index



(Base Period: March 1999)

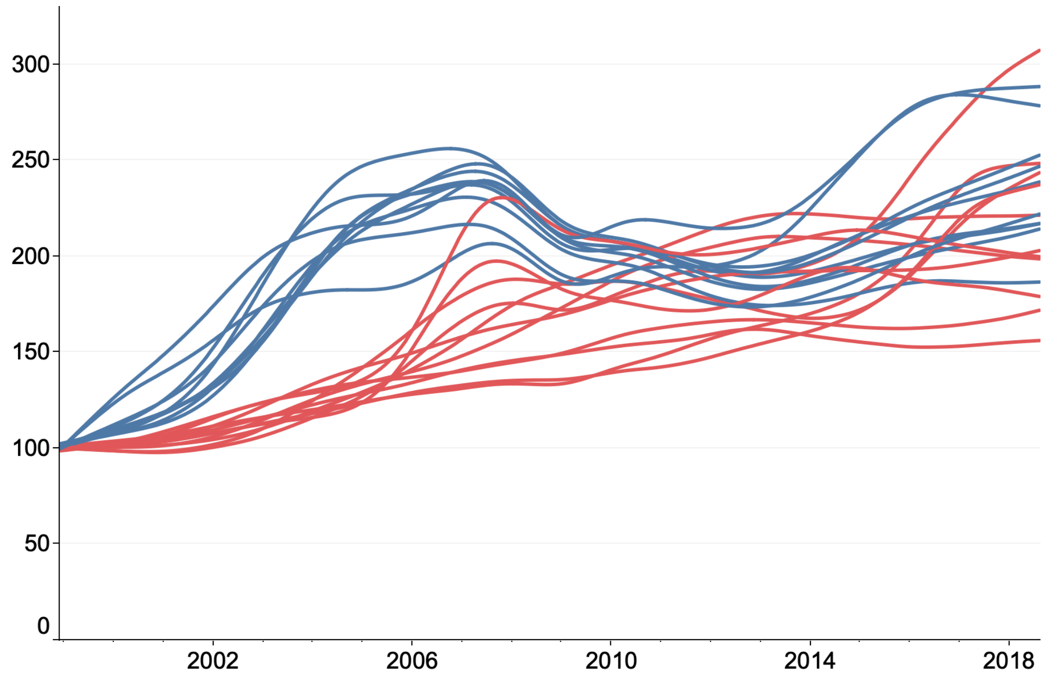
According to MacGee (2009), this is most likely due to the fact that mortgage loan requirements were not nearly as much relaxed as they were in the United Kingdom during that time. The only cities that show an comparably steep price increase during the late stage of the housing boom that occured in the UK are Calgary and Edmonton.

Notably, these two cities are the epicentre of the Canadian oil industry. Canada is the 6th largest oil producing country globally and ranks 3rd in available oil reserves (EIA, 2019), of which the majority is below the ground of Alberta, the province that Calgary and Edmonton are located in (NRC, 2014). Due to the resulting extended linkage of the economy of these two cities to an industry with a high systemic dependence, they are generally more likely to be impacted by systemic risk factors, of which the housing boom and the following financial crisis were some.

Most of the other cities experienced a steady increase of housing prices since March 1999. While most of the other cities in the sample show a steady increase in real house prices and a stagnation during the second half of the sample, there are notable steep increases in house prices to be observed for Vancouver, Toronto, Hamilton, and Victoria. Rherrad et al. (2019) examines the existence of real estate bubbles in Vancouver and Toronto, finding real estate price exuberance. Interestingly, Hamilton and Victoria are in comparably close proximity to Toronto and Vancouver, respectively, which hints at spatial spillovers of housing price developments in these areas.

Finally, 4.4 illustrates the overall sample to see how the house price development paths compare.

Figure 4.4: Sample - Real House Price Index



(Base: March 1999; Blue - UK, Red - Canada)

It can be seen that after the initially diverging paths due to the different characteristics of the housing markets in the period 2000-2008 described above, the house price indices of both countries move into similar territory. This is very valuable for the analysis. It insinuates that, firstly, the effect of the base period is not as pronounced anymore for both countries and, secondly, the differing repercussions of the period 2000-2008 increasingly vanish. The most recent developments of the sample suggest diverging house prices, per country and overall. This is a first clue for the heterogeneity of housing price development.

As this study sets out to explore the links between house price convergence levels and fundamental factors in light of the spatial utility framework, the last section of the data chapter describes the sources and properties of the fundamental factor data.

4.4 Fundamental Factor Data

Accumulating fundamental factor data on city level for multiple countries poses an even bigger challenge than for house price indices, as measurement methods can be quite varying from country to country. With that in mind, the data collected and used in the analysis is the best result to honour the features of the theoretical framework. Furthermore, data alignment is ensured by using either the same source for both countries or aligning the data with some modifications.

4.4.1 Growth in GDP per capita

For estimating wages, the method of Blanco et al. (2016) is to use GDP per capita as a proxy. Due to comparably uncomplicated calculation, this measure is readily available for every metropolitan area of the sample. The OECD metropolitan database comprises GDP per capita numbers for a vast sample of metropolitan areas on an annual basis. The numbers are adjusted for inflation and calculated for the overall population of each metropolitan area. The advantage of using this source is its adherence to the definitions of metropolitan areas that are described in section 4.3. As the regression analyses dynamic house price development, growth rates of GDP per capita are used. Despite need to use growth rates due to the estimation model, this also corrects for differences in purchase power per country.

4.4.2 Growth in Unemployment

The unemployment rate numbers of Canada stem from Statistics Canada and are indicative for the census metropolitan areas. For the United Kingdom, the ONS publishes numbers for business area clusters, which loosely align with the aforementioned definitions of metropolitan areas. The use of a growth rate corrects for level differences between the countries.

4.4.3 Growth in Population

For Canada, population figures are sourced from the statistical office 'Statistics Canada'. The numbers for the cities located in the United Kingdom stem from data accumulated by Eurostat, who use the OECD method to define metropolitan areas. For population, the use of growths rate corrects for level differences between the sample countries as well. Furthermore, the sample period accounts for the lagged explanatory variable in the estimation model.

4.4.4 Rainy Days per Month

Canadian climate data is sourced from weather measurement stations located in each city of the sample, published by the Canadian government. The ONS provides climate data for regions, which are interpolated on the cities within these regions.

The tedious inquiry and selection methods as well as alignments of measurements result in a well prepared dataset. The next section introduces the methodology used to apply the acquired data in the analysis.

5 Methodology

This chapter introduces the methodology used to detect house price convergence and to test the estimation model described in the theoretical framework. First, the convergence algorithm created by Phillips and Sul (2007) is described. Then, the methodology of the logistic regression model that is used to test the estimation model is explained.

5.1 Finding Convergence

Traditionally, an extensive amount of research uses cointegration-based techniques and unit root tests to examine long-run relationships between house price time series as well as between house prices and economic fundamentals. Evidence for house price convergence is then drawn from verifying cointegration of the investigated times series or the unit-root processes of them. Mathematically, a traditional model could test cointegration for two house price time series for individuals i and j in the following format:

$$p_{it} - p_{jt} = c_1 + c_2 t + \rho(p_{it-1} - p_{jt-1}) + e_t \, . \tag{5.1}$$

The model is then examined for a stochastic trend by testing whether $\rho < 1$, which would describe convergence of the two time series.
Traditional cointegration models often fail to account for heterogeneous idiosyncratic behaviour of individual observations in a sample. As a solution, Phillips and Sul (2007) introduce a model that works outside of a cointegration setup and accounts for heterogeneity in individuals growth paths. To account for individual heterogeneity, the authors model a new kind of growth element, δ, which has specific behavioural components. As a first step, Phillips and Sul take a time-varying single factor model

$$p_{it} = g_{it} + a_{it} \tag{5.2}$$

with p_{it} being house price indices. g_{it} denotes permanent components that determine cross-sectional dependence and a_{it} denotes transitory components. i is the individual observation and t is the observation time. To allow for heterogeneity in the model, it is necessary to separate permanent and transitory components from another by transforming the equation and setting p_{it} equal to

$$p_{it} = \left(\frac{g_{it} + a_{it}}{\mu_t} \right) \mu_t = \delta_{it} \mu_t \ . \tag{5.3}$$

μ_t is a single, time-varying common component and δ_{it} the long-run idiosyncratic convergence element measuring the share in μ_t of individual i at time t. μ_t is assumed to show trending behaviour that dominates a_{it} as $t \to \infty$. δ_{it} can vary in time and is modelled by Phillips and Sul (2007) as

$$\delta_{it} = \delta + \sigma \zeta_{it} L(t)^{-1} t^{-\alpha} \ , \tag{5.4}$$

with δ_i being fixed, ζ_{it} being weakly dependent over t but iid(0,1), and $L(t)$ being a slowly varying function for which $L(t) \to \infty$ as $t \to \infty$. α governs the rate at which the cross-sectional variation of the sample decays to zero over time. The decay rate α allows for heterogeneity in δ. If $\alpha \geq 0$, then δ_{it} converges to δ_i. Consequently, $\alpha \geq 0$ is then also the hypothesis of interest, as this would imply that the sample converges over time. The slowly varying function $L(t)$ corrects for further heterogeneity and ensures that convergence holds even at a small rate, for instance if $\alpha = 0$.

A mathematical illustration of the aim of the described principles of convergence in terms of house price indices p can be

$$lim_{t \to \infty} \frac{p_{it}}{p_{jt}} = 1 \tag{5.5}$$

for all i and j, which is, looking at 5.3 and 5.4, equivalent to

$$lim_{t \to \infty} \delta_{it} = \delta \ . \tag{5.6}$$

This initial modelling offers a new way to look at long run convergence and equilibria. The time varying model presented uses common stochastic trends to detect comovements in the long-run, without the utter necessity of classic cointegration. Due to the idiosyncratic attributes of the model, it also allows for transitionally heterogeneous behaviour of individuals as well as transition periods without comovement, which can be overlooked by cointegration approaches. According to Phillips and Sul, the algorithm enables the researcher to work with data sets of shorter time periods, as opposed to what is possible with cointegration methods.

5.1.1 Overall Convergence

Based on the derivation of the idiosyncratic convergence element, Phillips and Sul developed a regression procedure to test for the null hypothesis of convergence which is, as mentioned above, $H_0 : \delta_i = \delta$ and $\alpha \geq 0$. the alternative hypothesis is $H_A : \delta_i \neq \delta$, which implies that $\alpha \leq 0$.

Step 1:
In the first step, the cross-sectional variance ratio $\frac{H_1}{H_t}$ is constructed, where

$$H_t = \frac{1}{N}\sum_{i=1}^{N}(h_{it} - 1)^2 \; . \tag{5.7}$$

h_{it} represents a relative transition coefficient and is equal to

$$h_{it} = \frac{p_{it}}{N^{-1}\sum_{i=1}^{N} p_{it}} = \frac{\delta_{it}}{N^{-1}\sum_{i=1}^{N} \delta_{it}} \; , \tag{5.8}$$

which extracts information from the element δ_{it} relative to the panel average of it at time t. It therefore traces the transition path for i compared to the overall sample. H_t, the cross-sectional variance at point t, describes the average of the sum of the squared differences from all relative transition coefficients at t - it measures the quadratic distance for the panel from from perfect convergence. For perfect convergence, it must hold that $h_{it} \to 1$ for all i as $t \to \infty$. This implies that, looking at 5.7, it must hold that $H_t \to 0$ as $t \to \infty$ if there is perfect convergence. If perfect convergence does not hold, H_t might converge to a non-zero constant, or shows varying behaviour while staying above zero.

Step 2:
Phillips and Sul define the following regression equation to detect convergence:

$$log\left(\frac{H_1}{H_t}\right) - 2\log L(t) = \hat{a} + \hat{b}\log t + \hat{u}_t \tag{5.9}$$

$$\text{for } t = [rT], [rT+1], ..., T, \text{ with } r > 0 \quad .$$

Essentially, the equation tests the logarithm of the ratio between the initial cross-sectional variance and the cross-sectional variance at time t for all observations and all time periods. The coefficient $\hat{b}$ is equal to $2\hat{\alpha}$, with α stemming from equation 5.4. The size of $\hat{b}$ is therefore an indicator for the speed of convergence. If the null hypothesis of convergence, $\alpha \geq 0$, is rejected significantly, the sample diverges over time, which would mean that H_t increase over time relative to H_1. rT is a limitation on the time frame of the data, which is imposed for reasons explained in the analysis chapter.

Step 3:

An autocorrelation and heteroskedasticity robust one-sided t-test is applied to test the null hypothesis $\alpha \geq 0$. Aiming, for instance, for significance at a 5%-level, the null hypothesis is rejected when $t_{\hat{b}} < -1.65$. This would indicate overall divergence of the sample.

5.1.2 Club Convergence

A novelty in the model approach of Phillips and Sul is that rejection of the H_0 of convergence does not rule out convergence in subgroups of the individuals in the sample - the possibility of club convergence. This is a major improvement compared to traditional cointegration methods.

The analysis can go both ways. One might be looking at a sample of families in a neighbourhood and reject the convergence hypothesis for, as an example, a time-series of the yearly income (or any other variable that is worth to be tested for convergence). The test could then be rerun for subgroups of the sample, which are built according to attributes like household composition, education, etc.. While this application is possible, this might be also done with traditional cointegration methods. The actual novelty is that Phillips and Sul created a clustering algorithm that also works the other way around. It can detect subgroups of sample individuals that show convergence in, for instance, housing prices, without doing any pre-categorisation based on other attributes. This opens up the possibility to attain an unbiased view on house price convergence.

At this point, the methodology connects to theoretical framework. The clustering algorithm can detect subgroups of cities that show house price convergence. According to the spatial utility equilibrium model, one can state the hypothesis that if some cities converge to the same house price level, other utility-altering attributes of the cities might show alignment as well, as otherwise utility across space would not be in equilibrium. While similar hypotheses were successfully tested within single countries by application of this algorithm (Kim and Rous, 2012; Blanco et al., 2016; Holmes et al., 2019), past research lacks the international approach on city-level that this study takes on. Furthermore, the methodology in this study is directly based on the theoretical framework, while other papers offer little direct theoretical foundation.

Phillips and Sul extend the initial algorithm with a procedure to sort individuals into convergence subgroups, which is based on the already introduced regression method. The hypothesis is that, if the initial algorithm rejected overall convergence of the sample, there is still a possibility that convergence subgroups exist. As an example, there might be a sample, where the rejection of the overall convergence null H_0 implies that

$$H_A : b_{it} \rightarrow \begin{cases} b_1 \text{ and } \alpha \geq 0 & \text{if } i \in G_1 \\ b_2 \text{ and } \alpha \geq 0 & \text{if } i \in G_2 \,, \end{cases} \tag{5.10}$$

where G_1 and G_2 are convergence clubs and $G_1 + G_2$ is equal to the whole sample.

In the following, the necessary steps to detect convergence clubs are outlined.

Step 1:
The initial assumption is that a known core subgroup G_k exists, containing at least k members. To find the core group, the individuals first need to be ordered according to the last observation in the panel to ensure that the algorithm orders the convergence clubs by the found convergence level.

Step 2:
Select some k, with $N > k > 2$, of the highest individuals to form the core group G_k and calculate the convergence test statistic $t_k = t(G_k)$ by running the regression test described in the initial algorithm for the chosen group. Then, the core group size k^* is determined by maximising t over k:

$$k^* = \arg\max_k t_k \quad \text{subject to} \quad \min t_k > -1.65\,. \tag{5.11}$$

Choosing the core group by applying the equation $k^* = \arg\max_k t_k$ reduces the probability of a Type II error.

Step 3:
When the core group G_{k^*} is chosen, the other individuals are members of the imaginary complementary group $G^c_{k^*}$. Then, one member of $G^c_{k^*}$ at a time is added to the core group

G_{k^*}, followed by running the regression method from before on the whole group again. If the $\hat{t}$-statistic is above some critical value c, the individual becomes a member of the club. A recommendable value of c is equal to the critical value of the t-statistic at 5% significance, -1.65.
If by starting with the highest individuals, there is no core group G_k with $k = 2$ members to be found with the condition $\min t_k > -1.65$, the highest individual can be discarded when forming the core group.

Step 4:
Form a subgroup for all individuals for which $\hat{t} < c$ in step 3 and run the regression test on this subgroup. if $t_{\hat{b}} > -1.65$, there are two convergence clubs. If $t_{\hat{b}} < -1.65$, reproduce step 1-3 for this group. If there are no club members k with $t_{\hat{b}} > -1.65$ to be found, the conclusion is that all other individuals of the panel are divergent.

As an extension to the initial algorithm, Phillips and Sul (2009) introduce the optional process of rerunning the regression test on pairs of detected convergence clubs to examine whether some clubs might merge into larger clubs.

5.2 Analysing Fundamental Factors

Assuming that convergence clubs were found by application of the clustering algorithm in the last section, the next step is to examine the relationship of these convergence clubs to fundamental factors thereby test the validity of the spatial utility equilibrium model. Specifically, the interest lies in the influence that certain attributes of a city have for membership in a specific club. A classic linear model, as for instance an ordinary least squares (OLS) approach, would be inappropriate for this analysis. This is for the reason that - assuming there is an outcome with multiple convergence clubs - the dependent variable is categorical and non-continuous.
Instead, the approach taken follows similar research from other authors (Bartkowska and Riedl, 2012; Apergis and Payne, 2012; Kim and Rous, 2012), who are using a nonlinear logistic model approach. If two convergence clubs are detected, a binary logistic regression is sufficient. Otherwise, there arises a need for using a multinomial logistic regression. This section first explains the former, then the latter. The explanation of the logistic regression model is closely

linked to Wooldrige (2011) and Wooldridge (2016).

5.2.1 Binary Logistic Model

At its most basic, binary response models are used to predict the odds of binary outcomes. While there are obvious examples like a yes/ no answer to a question, the application corresponding to this research is the occurrence of two housing price convergence clubs in the sample of cities. Primarily, the aim is to model the conditional response probability $P(y = 1|\mathrm{x})$, where P is the probability, y is random and able to take up values 0 and 1, and $\mathrm{x} = (x_1, x_2, ..., x_k)$ is a vector of explanatory variables. While this setup also serves linear model approach, the interest lies in the extended form:

$$P(y = 1|\mathrm{x}) = G(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + ... + \beta_k x_k) = G(\mathrm{x}\beta) = p(\mathrm{x}) \;, \tag{5.12}$$

G is a nonlinear function of which the logit definition is

$$G(z) = \frac{e^z}{1 + e^z} = \Lambda(z) \;. \tag{5.13}$$

Then, $p(\mathrm{x})$ from equation 5.12 is indexed trough $\mathrm{x}\beta = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + ... + \beta_k x_k$, and G maps the index into the response probability. G is assumed to be a cumulative distribution function and can be derived from a 'latent variable model', with latent variable y^*:

$$y^* = \beta_0 \mathrm{x} + \epsilon \;. \tag{5.14}$$

The indicator function $y = 1[y^* > 0]$ is equal to 1 if $y^* > 0$ and equal to 0 otherwise. ϵ is symmetrically distributed around zero, which leads to $G(z) = 1 - G(-z)$ for all real numbers z. The derived conditional response probability for y is equal to $E[y|\mathrm{x} = P(y = 1|\mathrm{x}] = G(\mathrm{x}\beta)$.

In this way, only the effects of x_j on the latent variable $y*$ can be observed. Knowing that $E[y|\mathrm{x} = P(y = 1|\mathrm{x}] = G(\mathrm{x}\beta)$, it is apparent that the magnitudes of coefficient β are not useful for interpretation, as G is nonlinear. For a meaningful interpretation of the coefficients, the marginal effect of a variable x_j must be calculated. This then corresponds to a roughly continuous effect of it. The marginal effect is found by taking the partial derivative of x_j:

$$\frac{\partial p(\mathrm{x})}{\partial x_j} = g(\mathrm{x}\beta)\beta_j \text{ , where } g(z) = \frac{dG}{dz}(z) \,. \tag{5.15}$$

In the case of a logit model, the partial derivative of x_j is equal to

$$\frac{\partial p(\mathrm{x})}{\partial x_j} = \left(\frac{e^z}{(1+e^z)^2}\right)\beta_j \,. \tag{5.16}$$

The equivalent to this equation in a linear model would be simply a classic coefficient β_j. The assumption is that $g(z) > 0$ for all z in the logit model. This means that all partial effects have the same sign as their corresponding β. Furthermore, the relative effect of two variables x_i and x_j is the ratio of β_i and β_j. As an example, the marginal effect for an increase of x_1 by one unit is defined as:

$$G(\beta_0 + \beta_1(x_1+1) + \beta_2 x_2 + ... + \beta_n x_n) - G(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + ... + \beta_n x_n) \,. \tag{5.17}$$

For an estimation of the coefficients, standard OLS estimation is out of question, as the structure of the logistic model is non-linear. Instead, a logit model is usually estimated by an application of maximum likelihood estimation (MLE). There are two possible outcomes $P(y=1|\mathrm{x})$ and $P(y=0|\mathrm{x})$ and a conditional density (or 'likelihood') function

$$f(y|\mathrm{x}_i;\beta) = (G(\mathrm{x}_i\beta))^y[1-G(\mathrm{x}_i\beta)]^{1-y} \,, \tag{5.18}$$

which is monotonically transformed with a logarithm to create a maximisation equation that is more straightforward. Then, for observation i:

$$\ell_i(\beta) = y_i \log(G(\mathrm{x}_i\beta)) + (1-y_i)\log[1-G(\mathrm{x}_i\beta)] \,, \tag{5.19}$$

which is the log of the conditional density function of y_i, or the 'log-likelihood' of y_i. The maximum likelihood estimator $\hat{\beta}$ is then the result of maximising the sum of log likelihoods for all observations, or $L(\beta) = \sum_{i=1}^{n} \ell_i(\beta)$.

The logit estimator $\hat{\beta}$ for β is not a closed form solution, but usually estimated by a statistic program through routines that approximate the derivative of the maximum likelihood function.

5.2.2 Multinomial Logistic Model

A possible outcome of the club convergence algorithm presented above is a number of convergence clubs higher than two or, formally, a dependent variable that is not restricted to $y = 0, 1$. Instead, possible responses $P(y = j|\text{x})$ with $j = (1, 2, .., J)$ exist. Obviously, a binary response model would not suffice in this case, which is why the binary logit model needs to be extended to allow for more than two outcomes. Essentially, an outcome $y = h$ gets chosen as the base outcome. Then all other possible outcomes are separately regressed against it with a binary logistic approach. The model extension is called multinomial logistic regression.

In a multinomial logistic model, the response probability of outcome j is equal to

$$\mathrm{P}(y = j|\mathbf{x}) = \frac{e^{(\mathbf{x}\beta_j)}}{\left(1 + \sum_{h=1}^{J} \exp\left(\mathbf{x}\beta_h\right)\right)} = p_j(\mathbf{x}), \quad j = 1, \ldots, J \; , \tag{5.20}$$

where β_j is the coefficient of x_j.[12]

Equipped with the necessary tools to analyse the collected data, the next chapter applies the methodology to detect convergence patterns in the sample of housing prices and uses the logistic regression approach for the estimation model. The analysis part focuses on the technical execution, while the interpretation of the results follows in the interpretation chapter.

[12] The estimation of marginal effects within the multinomial logistic model is incredibly complicated. As a binary logistic model is estimated throughout the analysis section, the estimation of marginal effects will be restricted to the binary approach.

6 Data Analysis

In this chapter, the first step is to check for overall convergence of housing prices of the sample cities over time by applying the method of Phillips and Sul (2007). After testing and rejecting overall convergence, the clustering algorithm (section 5.1.2) finds three convergence clubs. Consequently, the multinomial logistic regression is used to detect relations between fundamental common factors and the convergence clubs. In a second step, the attempted merging of the initial convergence clubs condenses the outcome to only two convergence clubs. This opens up the possibility to test the fundamental common factors again on this slightly different outcome to further validate the results from the first step. Consequently, the binomial logistic regression is applied to check whether the results from the first step hold up in the new setting. The purpose of the analysis chapter is acquiring and validating results, while the interpretation in light of the spatial equilibrium model will follow in the next chapter.

6.1 Convergence Analysis

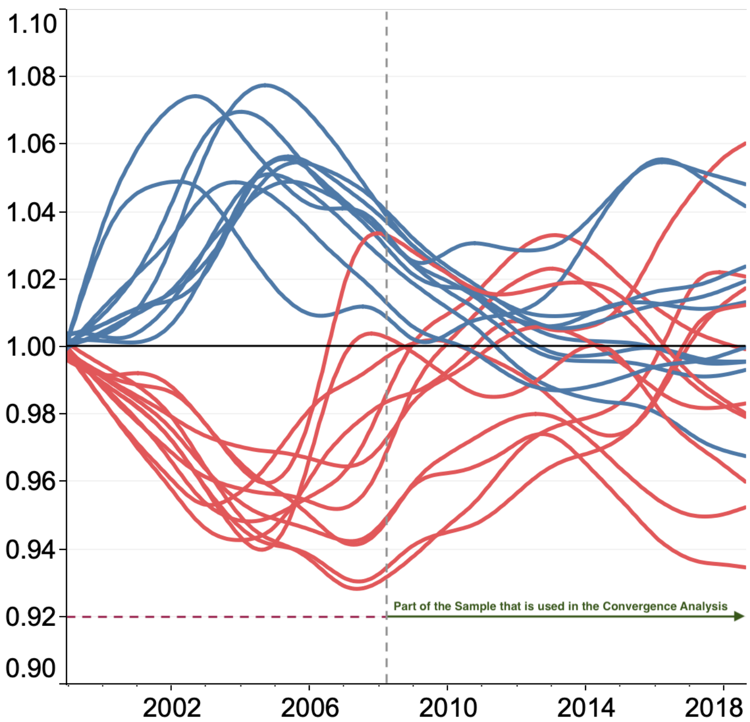
In this section, the convergence algorithm of Phillips and Sul (2007) is applied to the sample of house price indices. First, the algorithm is used to test for overall convergence. Afterwards, the clustering method is applied to potentially find convergence clubs.

6.1.1 Overall Convergence

Before presenting the estimation results, a special issue regarding the sample demands an explanation. As described in step 2 of the convergence algorithm (Section 5.1.1), Phillips and Sul (2007) recommend to discard some fraction r from the beginning of the time series sample. Their argument is, connected to general growth convergence analysis, that it helps the algorithm to focus on what happens when the sample housing prices grow larger and values eventually disperse more clearly. To get a graphical expression of this, one can observe the relative transition coefficients h_{it} over time in figure 6.1. In the beginning of the sample, all

h_i are equal to one.[13] The paths taken in the first half of the sample give no indication of the transitional patterns that can be discovered towards the end of the sample period. This is a graphical representation of the disappearance of the base period effect, which stems from the fact that all time-series in the sample start at the same value in March 1999. The initial divergence that can be observed in the first half of the of figure 6.1 is related to the vastly different impacts of the real estate boom in the years up until 2009 on each country, which are explained in detail in chapter 4. There is general alignment of the relative transition coefficients afterwards, then increased overall dispersion towards the end. To avoid the distortions of the base period effect and the real estate boom, as well as to honour the recommendation of Phillips and Sul for their own algorithm, the consequence is to follow Kim and Rous (2012) and apply the convergence algorithm on the second half of the sample only. Consequently, the algorithm itself uses monthly data from January 2008 until November 2018.

Figure 6.1: Sample - Transition Paths h_t

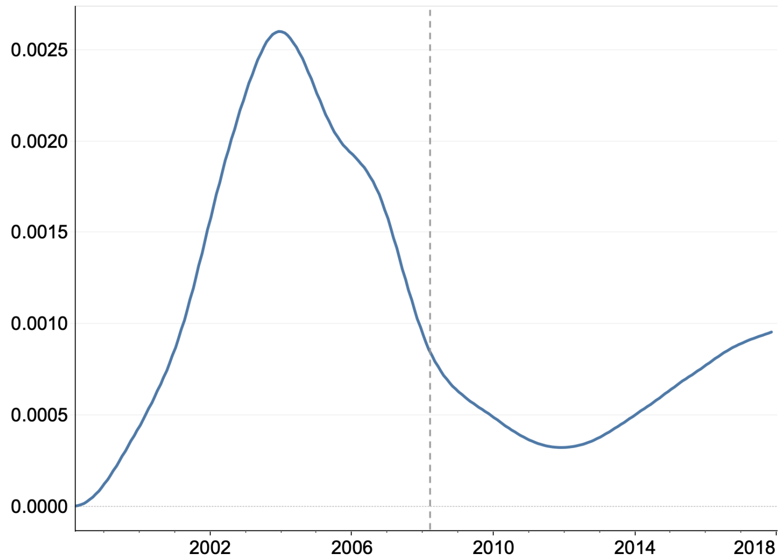


Note: The figure plots the relative transition coefficients over time according to $h_{it} = p_{it}/(N^{-1}\sum_{i=1}^{N} p_{it})$. p_{it} is the Hodrick-Prescott trend log house price index for sample individual i at time t. Divergence from 1 indicates divergence of the dedicated i relative to the overall sample.
Blue: United Kingdom Cities; Red: Canadian Cities
Sample Period: March 1999 - November 2018

[13] As the index is at the base for all cities and $h_{it} = p_{it}/(N^{-1}\sum_{i=1}^{N} p_{it})$ equals 1 for each i at the base period.

For an analysis of overall convergence of the sample, the process described in chapter 5 (Section 5.1.1) is utilised. The first step is to calculate the values for cross-sectional variance H_t over time.

Figure 6.2: Full Sample Cross-Sectional Variance H_t



Note: The figure plots the overall cross-sectional variance of the full sample according to the formula $H_t = \sum_{i=1}^{N}(h_{it} - 1)^2/N$. An increasing curve indicates increasing overall divergence within the sample.

Figure 6.2 is a graphical representation of the overall cross-sectional variances H_t. It still includes the part of the sample that is not used in the algorithm for illustrative purposes. The higher H_t, the weaker is the case for overall transition at t. As expected, the value increases during the real estate boom period and adjusts to a lower level in the time period where the removed part of the sample ends. In the period after that, cross-sectional variance seemingly increases, which implies increasing overall divergence of house prices across the sample cities over time.

This statement is tested by performing the regression test described in 5 (Section 5.1). As described earlier, there is overall divergence in the sample if the null hypothesis of $\alpha \geq 0$, as part of $\hat{b} = 2\hat{\alpha}$ in the regression equation, is rejected.

The results are presented in table 6.1. The estimate $\hat{b}$ is negative, which suggests overall divergence of house prices in the sample of cities. Furthermore, the t-statistic leads to rejection of convergence not just at a 5%, but actually at a 1% level for the sample of cities. This fits the initial impression from figure 6.1 and leads to the conclusion that there is no evidence for convergent behaviour of housing prices in the overall sample of cities.

Table 6.1: Sample Convergence Regression Results

log(t) regression			
$\hat{b}$	*std. err.*	$t_{\hat{b}}$	*p-value*
-1.0001890	0.2696097	-3.7097610	0.0001037

Note: Regression of $log\left(\frac{H_1}{H_t}\right) - 2\log L(t) = \hat{a} + \hat{b}\log t + \hat{u}_t$, as explained in the methodology.
H_0: $\alpha \geq 0$, which equals convergence. Reject H_0 of convergence when $t_{\hat{b}} < -1.65$, which indicates divergence.

6.1.2 Club Convergence

As statistical evidence of overall convergence is rejected, the clustering algorithm (section 5.1.2) is applied to detect potential convergence in subgroups. After ordering the sample of cities by the last observation according to Step 1, the number of members k^* of the core group G_k^* needs to be found. By maximising k^* according to the criterion $\min t_k > -1.65$ of step 2, three cities - Vancouver, Brighton, and London - are part of the core group.
Step 3 of the clustering algorithm identifies further members of the core group. The only new members to be found are Toronto and Hamilton. With the cities left, the recursive mechanism outlined in step 4 is applied to find further convergence clubs. Table 6.2 shows the results of the clustering algorithm for the sample.

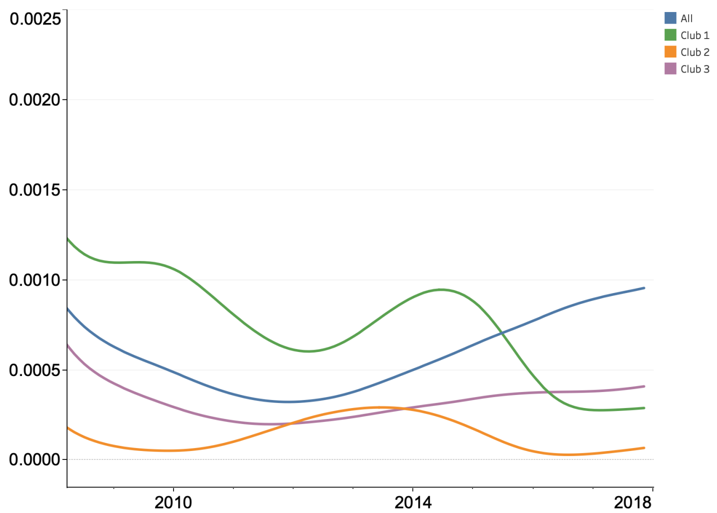
The upper part shows each club and the members. Below the line, the regression coefficient, the standard errors, and the corresponding t-statistic are shown. Club 1 has five members; the positive regression coefficient as well as the t-statistic way above -1.65 are evidence for the fact that the null of convergence cannot be rejected. This is the clearest result of all three clubs.
The second club - consisting of five members as well - clearly fails to reject the null of convergence too, albeit with less strong values than for club 2.
The weakest performance is shown by club 3, which has eleven members. The slightly negative β hints at divergence. Nevertheless, this result is insignificant even at a 10% level, which leads to the conclusion that the members of the club do not show significant divergence from each other.
Figure 6.3 illustrates the cross-sectional variance of the log house price indices H_t for each club compared to the overall sample variance. The dynamics depicted in figure 6.3 graphically fit the estimations of the clustering algorithm. The cross-sectional variance of the three individual

Table 6.2: Convergence Club Classification

Convergence Clubs			
	Club 1	*Club 2*	*Club 3*
	(5)	(5)	(11)
	Vancouver	Leicester	Birmingham
	Brighton	Manchester	Leeds
	London	Victoria	Sheffield
	Toronto	Nottingham	Newcastle
	Hamilton	Winnipeg	Montreal
			Edmonton
			Quebec
			Liverpool
			Calgary
			Ottawa
			Halifax
$\hat{b}$	1.4248	0.1584	-0.3648
std. err.	0.0209	0.0633	0.3729
t_b	68.127	2.504	-0.978
p-value	1	0.9939	0.1639

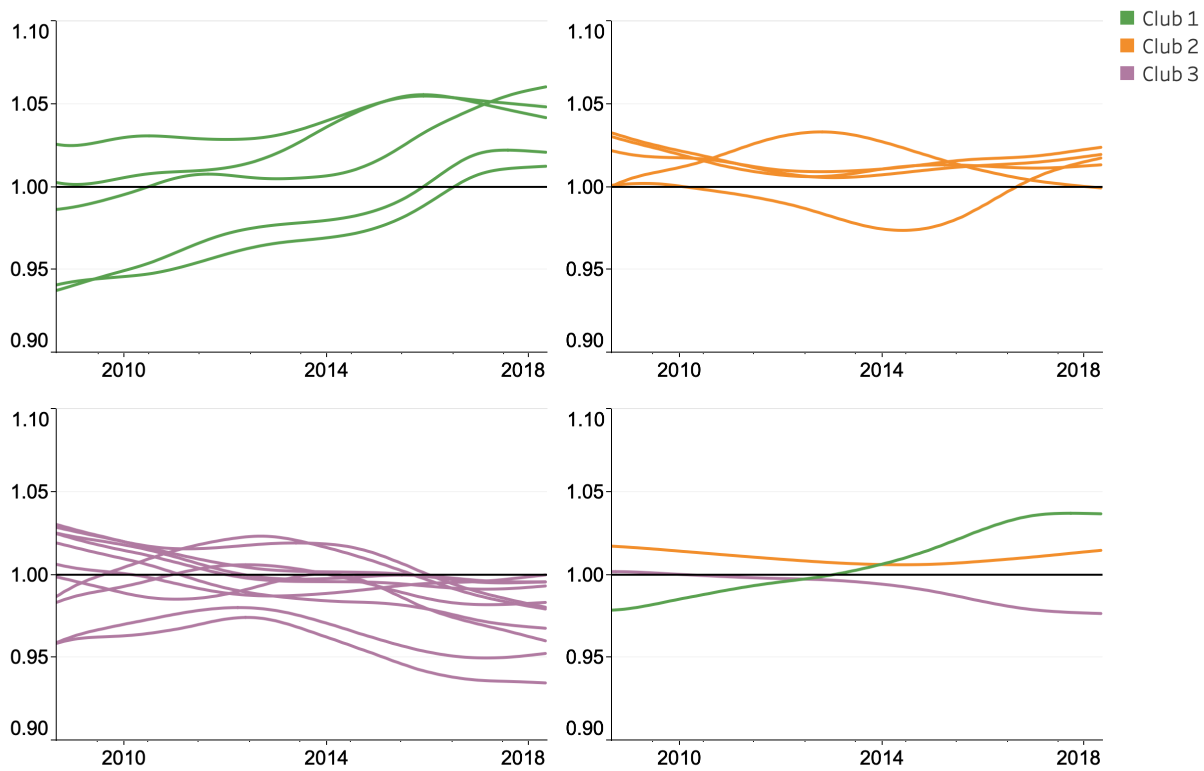
Note: Application of clustering algorithm (section 5.1.2).
H_0: $\alpha \geq 0$, which equals convergence. Reject H_0 of convergence when $t_{\hat{b}} < -1.65$, which indicates divergence.

Figure 6.3: Cross-Sectional Variance H_t per Club



Note: The figure plots the overall cross-sectional variance H_t of the full sample as well as for each club individually. An increasing curve indicates increasing overall divergence. (Jan 2008 - Nov 2018) clubs are well below the one of the overall sample. The graph illustrates excellently the principle of operation for the algorithm, as it uses the progression of the cross-sectional variance over time to predict the convergence tendency in the future. Therefore, while the variance of club 1 is consistently higher than the one of club 2, the reduction of variance over time is stronger. The clustering algorithm therefore predicts a stronger path of convergence for club 1 than for club 2. Club 3 has a lower dispersion parameter H_t at most points in time, but the graphs shows a tendency of divergence towards the end of the sample period. Still, the line settles markedly below the overall sample line, which is coherent with the estimation results in table 6.2 that fail to reject convergence for clubs 3.

Figure 6.4: Transition Paths h_t per Club, relative to the Overall Sample



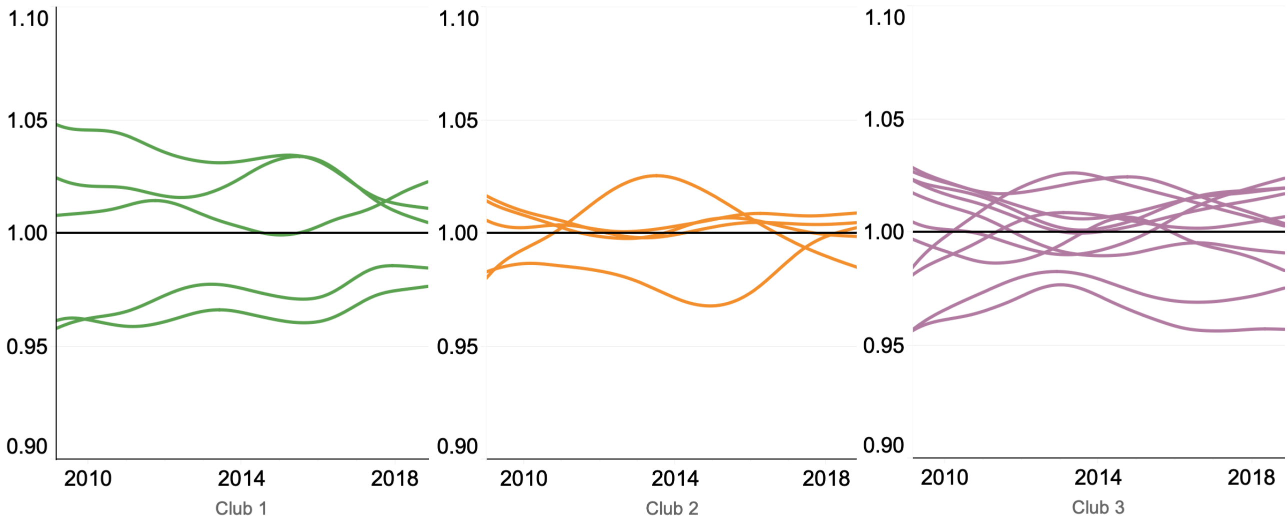
Note: The figure plots relative transition paths h_{it} for each club member, relative to the overall sample (compare to curves in figure 6.1) for the part of the sample that is included in the algorithm. The fourth graph shows the average transition paths per club. The higher the curve, the higher is the expected level of house price appreciation.

To get a more detailed look of the convergence patterns within each club, figure 6.4 offers an overview of the individual transition paths h_t for each member of each club relative to the

overall sample. Furthermore, a comparison of the average paths is depicted in the lower right graph. Club 1 and club 2 confirm the estimation results as well as the explanations of figure 6.3. The individual relative transition paths seem to converge towards a similar direction over time. Only the two cities with the lowest transition paths of club 1 initially seem to be less a member of club 1 than club 2. Again, this is explained by the fact that, while the initial gap to the other members of the club is quite high, the two cities show a clearer tendency to align with members of club 1 than they do with members of club 2 due to very steep transition paths. They are therefore expected to catch up with the other members of club 1 asymptotically and would therefore diverge from members of club 2 in the future.
While the members of club 3 have transition paths that are trending below unity, it is less apparent whether the house price indices of this club converge to a similar value in the long run. This less clear result matches the estimation results in table 6.2. The comparison of the average h_t per club relative to the whole sample in the lower right is as expected, as club 1 reflects higher transition paths than the two others and the long term perspective of club 3 is below the two others. One can see in this graph why overall convergence was rejected for the whole sample, as the divergence between the clubs is very much apparent.
Finally, Figure 6.4 depicts excellently the nature of the three convergence clubs. The members of club 1 converge to the highest level of housing prices, club 2 has the middle ground and members of club 3 tend to trend to a comparably lower level. To get a better impression of the converging behaviour within the convergence clubs, figure 6.5 shows the individual development paths of h_t relative to the other club members only. Then, taking $h_{it} = \frac{p_{it}}{N^{-1}\sum_{i=1}^{N} p_{it}}$ from before, strong club convergence implies that h_t would tend to unity for all members. Again, the transition paths of club 1 are comparably clear. While club convergence is evident, the dynamics that lead to club convergence vary among members. The two cities that have relatively low initial states compared to the other members and catch up over time are Toronto and Hamilton. The two upper members that seem to move together towards the end of the time sample are London and Brighton. The fifth one, Vancouver, has an increasing transition path towards the end of the time sample. This is due to the steep house price increase that can be seen in the house price graph in the data chapter.

Club 2 shows heterogeneous dynamics as well, with three club members (Leicester, Manchester, and Nottingham) moving almost homogeneously compared to the other two.

Figure 6.5: Transition Paths h_t per Club, relative to Club Members only



Note: The figure plots relative transition paths h_{it} for each club member, relative to the other club members only. Clearer movements of curves to unity indicate a stronger convergence pattern of house prices within a club.

Although the members of club 3 show comparably clear downward transition tendencies relative to the whole sample in figure 6.4, the relative transition behaviour among members of club 3 is not as neat. Evaluating all members of club 3 together, the impression is that the evidence for convergence within the club is rather weak. Nevertheless, the overall convergence pattern is distinct from the other two groups.

Figure 6.6 displays the club memberships of the sample cities on a map. Club membership in the UK seems to be related to location. Members of club 1 are located in the south, while members of club 3 are dominant in northern England and club 2 dominates the space in-between. Geographically, the picture is much less clear in Canada. While the close proximity of Toronto and Hamilton as members of club 1 resembles London and Brighton, Vancouver is a main outlier located on the other side of the country. Members of club 3 are concentrated at the east coast and the inner mainland. Club 2 does not seem to be bound by location, with one member at the east coast and one member in the middle of the country.

House price indices in Canada and the UK do not show overall growth convergence, but subgroups with significant convergence behaviour exist. According to the spatial utility equilibrium theory, the significant differences in the level of housing prices that these clubs converge to must go along with differences in the behaviour of other utility-altering variables. Therefore, the next

Figure 6.6: Map of Convergence Club Members

step is to test the impact that fundamental factors have on club membership. For that purpose, a multinomial logistic regression is applied in the next section.

6.2 Fundamental Factor Analysis

6.2.1 Sample Size Discussion and Model Validity

As already mentioned in the data chapter, acquiring comparable data on regional or city level for two countries at once poses a big challenge. At the same time, the sample of metropolitan areas - while carefully selected and made fit for analysis - is comparably small. This limits the amount of independent variables that can be used in a logistic regression. The optimal minimum number of events per variable[14] (EPVs) for logit models is an ongoing topic that is mostly discussed in the sphere of medical sciences. While there is consensus that a higher sample size is beneficial, the minimum EPV is a matter of debate, as can be seen in Vittinghoff and McCulloch (2007), Van Smeden et al. (2016), Austin and Steyerberg (2017), Jong et al. (2019), and others.

The consequence of a low sample size in a logistic regression is the possibility of overfitting of the model. Overfitting occurs when, due to a low sample size, the model is representative of the sample but not indicative for the whole population. However, this argumentation is not directly applicable to this study. In medical research, an estimation based on a sample of 21 individuals might not be indicative for the world population. However, a study of metropolitan areas has a fairly limited statistic population and the actual number of metropolitan areas in the sample countries of this study is well represented by the cities chosen.

A possible consequence of overfitting are arbitrarily high coefficients for significant variables. It is worth pointing out that Kim and Rous (2012) as well as Blanco et al. (2016) find inflated coefficients for significant variables in their approaches, even with comparably larger samples of metropolitan areas or regions.[15]

[14]Specifically, for a binary logistic regression, the number of events per variable is the smaller one of the number of subjects who experienced the outcome and the number of subjects who did experience the other outcome, according to Austin and Steyerberg (2017). For multinomial logit models, the number of events per variable is the smaller of the number of subjects who did experience the base outcome and the number of subjects who did experience one of the other outcomes, according to Jong et al. (2019).

[15]There are multiple extensions to logistic regression methods that supposedly improve results for small sample

To diminish potential overfitting, the estimation follows a 'general-to-specific' approach. The logistic regression is first executed with all independent variables included. Then, variables with insignificant coefficients are removed to find further proof of validity for significant ones.

To judge the validity of the model, multiple values given in the regression output are of help. In this specific case, watching the confidence intervals is of importance, as they give a good impression whether the estimated coefficient is actually based on a meaningful distribution and not on a distorted sample. The Likelihood Ratio Chi square test ($LR\chi^2$) tests for all equations of the multinomial logit model whether at least one of the estimated coefficients is significantly different from zero. The interpretation is simplified by the reported probability (p-value) of the null hypothesis, which is equal to no effect of any estimated coefficient on the dependent variable.
As the real R^2-value cannot be calculated for non-linear models, the statistic program used reports a so-called pseudo-R^2. As it is an approximation value and supposed to be interpreted with great caution generally, it is not likely to be a good metric to evaluate a model with a low sample size.

6.2.2 Multinomial Logistic Regression

The multinomial logistic regression model is estimated to predict how city-specific variables that are consistent with the spatial utility equilibrium approach affect the probability that a city is found to be a member of a specific convergence club.[16] The base outcome is club 3. Additionally, a country dummy is added to the model to correct for fundamental differences between the sample countries.

The results of the multinomial logit model regression for the city sample are presented in table 6.3. The first direct observation is that all coefficients are positive and increase when comparing

sizes (penalised logistic regression and exact logistic regression methods). An application of these methods does not improve results significantly. Furthermore, the estimation commands of these models leave out important regression results that are needed to validate the results (e.g. confidence intervals). For these reasons, it is more valuable to use a classic logistic regression model and analyse it with proper judgement, also to ensure transferability and comparability of the results.

[16] If the variable convergence club is denoted by C, the probability equation is then:
$\mathrm{P}(C = j|\mathbf{x}) = \frac{e^{(\mathbf{x}\beta_j)}}{\left(1+\sum_{h=1}^{J}\exp(\mathbf{x}\beta_h)\right)} = p_j$, analogue to equation 5.20 from the methodology chapter.

Table 6.3: Multinomial Logistic Regression Results

		Base = Club 3	
Variable		Club 1	Club 2
GDP per capita Growth			
	Coefficient	13.22	7.98
	std. err.	(7.12)	(4.74)
	p-value	0.06	0.09
	conf. Interval	-0.73 | 27.17	-1.31 | 17.26
Unemployment Rate Growth			
	Coefficient	1.32	0.97
	std. err.	(0.85)	(0.63)
	p-value	0.18	0.13
	conf. Interval	-0.53 | 2.76	-0.27 | 2.20
Population Growth			
	Coefficient	12.65	5.76
	std. err.	(7.41)	(5.68)
	p-value	0.09	0.31
	conf. Interval	-1.87 | 27.18	-5.38 | 16.91
Rain			
	Coefficient	1.15	0.63
	std. err.	(1.00)	(0.86)
	p-value	0.25	0.47
	conf. Interval	-0.81 | 3.11	-1.06 | 2.31
Constant			
	Coefficient	-19.17	-8.71
	std. err.	(10.69)	(7.06)
	p-value	0.07	0.25
	conf. Interval	-40.09 | 1.78	-22.02 | 5.67
		log-likelihood	-10.73
		LR χ^2	21.48
		p > χ^2	0.02
		Pseudo R^2	0.50

Note: The country dummy is significant and excluded.

club 1 relative to the base versus comparing club 2 relative to the base. This strengthens the overall credibility of the results, as it is to be expected that the differences of club 1 to club 3 should be larger than in a comparison of club 2 and club 3. The signs for the coefficients of GDP per capita growth and population growth are positive, as expected, and significant - with the exception of the population growth coefficient for club 2. The coefficient for unemployment rate growth is neither significant nor has the expected sign. Furthermore, the coefficient for the average of rainy days per month is insignificant as well. The likelihood ratio test shows an overall significance of the model, which means that the coefficients for GDP per capita growth and population growth are explanatory.

As expected, the coefficients of the significant variables are quite inflated. Nevertheless, the confidence intervals of all positively significant coefficients confirm that the results are based on a valid distribution. All significant variables are significant on a 10% level. Albeit this is not a strong degree of significance, it has to be seen in light of the sample size and the resulting variance of the results. A higher level of significance would hinge on just a few observations that behave differently, which can easily lead to a situation were one variable is perfectly explaining the outcome of the dependent variable. This would then weaken the power of the overall estimation results. Taking this into account, a significance at 10% should be judged as powerful.

As argued above, decreasing the number of independent variables in the regression would most likely increase the stability of the model. Therefore, a limited model is estimated, without unemployment growth as well as the average rainy days per month. The results are reported in table 6.4.

Overall, the results seem to be in line with the full model approach estimated before. Notably, the overall fit of the model is better, with a log likelihood of greater power and an increased overall model significance according to the $LR\chi^2$ test. While the significance of GDP per capita growth is very similar to the full model, population growth shows increased power aside from the fact that the coefficient for club 2 is still insignificant.

Overall, the preliminary result is that cities with higher growth in GDP per capita have a higher probability that a city is a member of convergence club 2 relative to club 3, and even more so for club 1 relative to club 3. This means that higher GDP per capita growth is clearly related to higher house price convergence levels. Weaker evidence is found for population growth; an

Table 6.4: Limited Multinomial Logistic Regression Results

	Base = Club 3	
Variable	Club 1	Club 2
GDP per capita Growth		
Coefficient	6.31	3.43
std. err.	(3.26)	(2.09)
p-value	0.05	0.1
conf. Interval	-0.08 | 12.71	-0.66 | 7.52
Population Growth		
Coefficient	7.39	3.44
std. err.	(3.89)	(2.09)
p-value	0.06	0.19
conf. Interval	-0.22 | 15.01	-1.74 | 8.62
Constant		
Coefficient	-10.59	-4.58
std. err.	(5.05)	(2.78)
p-value	0.04	0.1
conf. Interval	-20.48 | -0.70	-10.04 | 0.88
	log-likelihood	-13.45
	χ^2	16.02
	p $> \chi^2$	0.01
	Pseudo R^2	0.37

Note: The country dummy is significant and excluded.

increase in population growth is related to higher house price convergence levels only for club 1 relative to club 3.

The clustering method of Phillips and Sul is quite strict in the estimation of convergence clubs, as pointed out by themselves as well as multiple other authors. Furthermore, as discussed at length above, a main disadvantage of the small sample size for the regression is the potentially small number of events per variable (EPV). A smaller number of possible events - in the case of this study, a smaller number of clubs - could potentially increase the number of events and create more robust results. For this reason, the next step is to apply the club merging method described in chapter 5.

6.2.3 Club Merging

As described in chapter 5, the club merging procedure is to rerun the regression test of the initial club convergence method on pairs of clubs, testing for potential common convergence of the tested pairs. The detailed results of this procedure are reported in table 6.5. Club 1 and club 2 merge and create a new club, which is called club A. Club 3 remains untouched and is now called club B. As there are two clubs now, the binomial logit model can be applied for potentially further improvement of the model and validation of the results.

The newly created club A fails to reject the null hypothesis of convergence with slightly weaker values than for former club 1, but stronger than for former club 2 - which is expected. As the newly created club B is equal to club 3, the estimated values are equivalent to the estimated coefficients from before as well, which means that there is still no evidence for divergence.

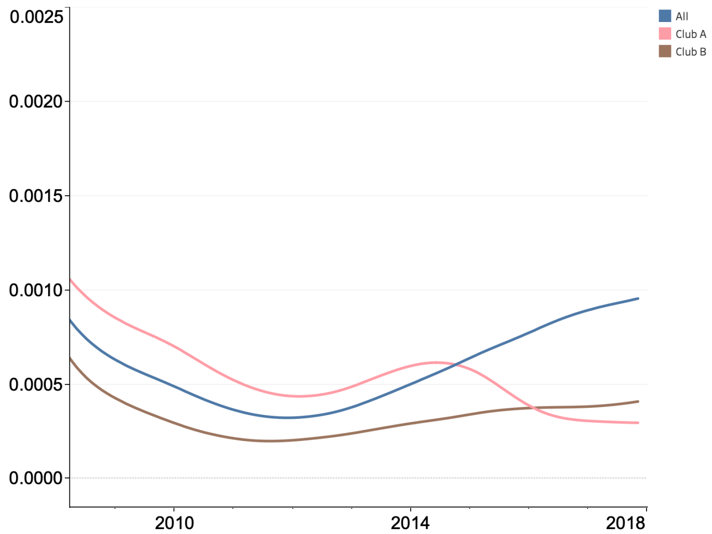
For extended comparability to the initial club convergence results, familiar graphs from the initial convergence club analysis are set up once again. The behaviour of the cross-sectional variance in H_t for each house price convergence club can be seen in figure 6.7. Club B obviously has the same cross-sectional variances over time as club 3. As club A consists of former club 1 and club 2, the curve does not show the same downward tendency as before. Overall, both clubs move still markedly below the cross-sectional variance of the whole sample. The comparison of the relative transition paths in figure 6.8 give a similar impression. While the transition paths of the members of club B are equivalent to club 3, club A combines the transition paths of club

Table 6.5: Merged Convergence Club Classification

Merged Convergence Clubs		
	Club A	*Club B*
	(10)	(11)
	Vancouver	Birmingham
	Brighton	Leeds
	London	Sheffield
	Toronto	Newcastle
	Hamilton	Montreal
	Leicester	Edmonton
	Manchester	Quebec
	Victoria	Liverpool
	Nottingham	Calgary
	Winnipeg	Ottawa
		Halifax
$\hat{b}$	1.0559	-0.3648
std. err.	0.102	0.3729
t_b	103.485	-0.978
p-value	1	0.1639

Note: The country dummy is significant and excluded.
Club A: Club 1 + Club 2
Club B: Club 3

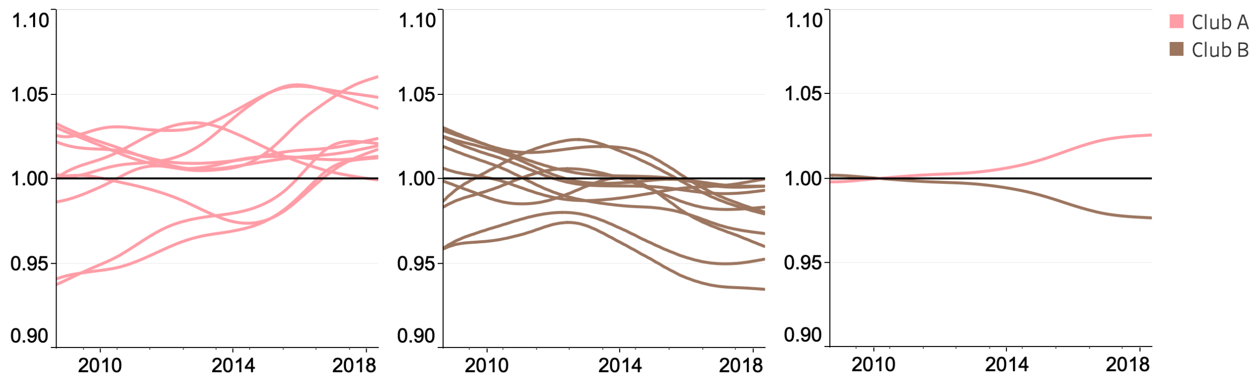
Figure 6.7: Cross-Sectional Variance H_t per Merged Club



Note: The figure plots the overall cross-sectional variance H_t of the full sample as well as the H_t for each club individually. An increasing curve indicates increasing overall divergence.

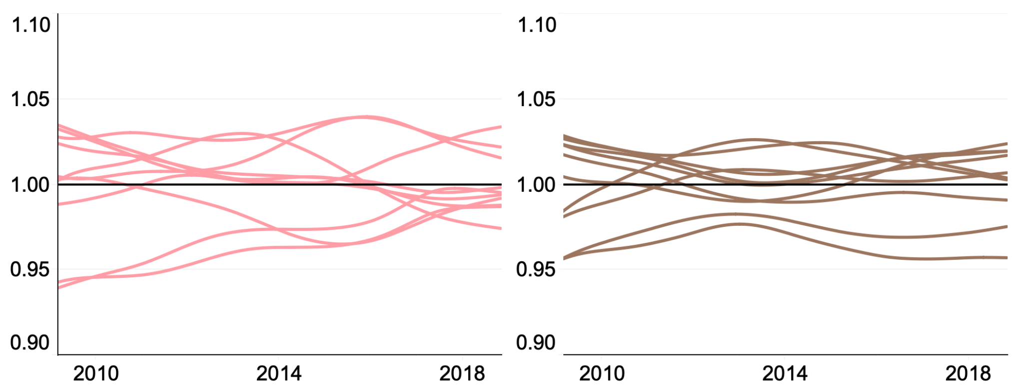
1 and club 2. Once again, the divergence of the average transition paths h_t per club show why overall sample convergence was rejected in the beginning of the analysis. Figure 6.9 displays the transition paths h_t relative to only the club members. Despite the fact that the members of club B show, equivalent to club 3, a rather weak picture of convergence, it can be observed that the newly formed club A shows a clearer performance, as the members seem to converge to unity asymptotically.

Figure 6.8: Transition Paths h_t per Merged Club, relative to the Overall Sample



Note: The figure plots relative transition paths h_{it} for each club member, relative to the overall sample (compare to curves in figure 6.1) for the part of the sample that is included in the algorithm. The fourth graph shows the average transition paths per club. The higher the curve, the higher is the expected level of house price appreciation.

Figure 6.9: Transition Paths h_t per Merged Club, relative to Club Members only



Note: The figure plots relative transition paths h_{it} for each club member, relative to the other club members only. Curves that show clearer movements to unity indicate stronger convergence of house prices within a club.

As the initial three clubs are now shrunk to two, there is an opportunity to apply a binomial logistic regression to test the sample again and add validity to the results.

6.2.4 Binomial Logistic Regression

A binomial logistic regression estimates logarithmic odds for the outcomes 1 vs. 0. The assumption is that being a member of club A is equivalent to the outcome 1 and being a member of club B is equal to 0. The results of the binomial logistic regression are presented in table 6.6. The most intriguing result is that GDP per capita growth is better behaved than in the previous multinomial estimations, being significant at a 5% level now. The coefficient for unemployment growth is still insignificant, but comes closer to significance. The coefficient for the average rainy days per months is still insignificant.
There is a more impactful change for population growth, of which the coefficient is insignificant now with a comparably high standard error. This was already the case in the multinomial regression, but the added fact that the coefficient now shows a lack of significance even at the 10% level might points in the direction that population growth is at least not relevant in the full model.
Therefore, two limited models are estimated: one with population growth included and one without it. This is the best attempt to refine the previous multinomial estimations and honour the initial binomial results at the same time. Additionally, the average marginal effects of the variables are estimated.

Table 6.7 presents the results of both the estimation with and without population growth. The log-likelihood is improved compared to the full binomial model in both approaches. While the model without population growth has a marginally better log-likelihood than the more limited approach, the model including both GDP per capita growth and population growth rejects the null of the LR χ^2 more firmly. The coefficients themselves, while still positive, are lower than in the full model. This enhances credibility of the model slightly, as the coefficients come closer to reality. The model that includes population growth shows significancy for both coefficients.

Lastly, the estimated average marginal effects are reported. In the model including population growth, it can be observed that an increase of one percent in GDP per capita growth increases

Table 6.6: Binomial Logistic Regression Results

Variables		
GDP per capita Growth		
	Coefficient	9.08
	std. err.	(4.68)
	p-value	0.05
	conf. Interval	-0.095 | 18.26
Unemployment Rate Growth		
	Coefficient	0.96
	std. err.	(0.60)
	p-value	0.11
	conf. Interval	-0.22 | 2.14
Population Growth		
	Coefficient	7.73
	std. err.	(5.40)
	p-value	0.152
	conf. Interval	-2.84 | 18.31
Rain		
	Coefficient	0.78
	std. err.	(0.83)
	p-value	0.344
	conf. Interval	-0.84| 2.40
Constant		
	Coefficient	-10.49
	std. err.	(6.81)
	p-value	0.124
	conf. Interval	-23.84 | 0.71
log-likelihood		-5.68
LR chi		17.71
p > chi2		0.00
Pseudo $\hat{R2}$		0.61

Note: The country dummy is significant and excluded.

the probability to be in club A by 49%, the convergence club that converges to a higher level of housing prices. In the regression without population growth, the average marginal effect is equal to 75%. Similarly, a one percent increase in population growth increases the probability of being in club A by 52%. These are striking results. While the values might be upwardly biased due to the initially high regression coefficients, the values are highly significant. GDP per capita growth as well as population growth lead to a higher probability for a city to be in a convergence club that converges to a higher level of housing prices.

Table 6.7: Limited Binomial Logistic Regression Results

	Coefficients		Average Marginal Effects	
Variable	(1)	(2)	(1)	(2)
GDP per capita Growth				
Coefficient	4.87	4.18	0.75	0.49
std. err.	(2.35)	(2.06)	(0.17)	(0.15)
p-value	0.04	0.04	0.00	0.00
conf. Interval	0.25 | 9.48	0.15 | 8.22	0.42 | 1.08	0.20 | 0.78
Population Growth				
Coefficient	-	4.49	-	0.52
std. err.	-	(2.59)	-	(0.20)
p-value	-	0.08	-	0.01
conf. Interval	-	-0.58 | 9.56	-	0.12 | 0.92
Constant				
Coefficient	-1.72	-5.52	-	-
std. err.	(1.08)	(2.81)	-	-
p-value	0.11	0.05	-	-
conf. Interval	-3.84 | -0.40	-11.02 | -0.02	-	-
log-likelihood	-9.72	-7.79		
LR χ^2	9.62	13.49		
p > χ^2	0.01	0		
Pseudo R^2	0.33	0.46		

Note: The country dummy is significant and excluded.
(1): without pop. growth
(2): with pop. growth

6.3 Summary of Estimation Results

There is no evidence of convergent behaviour of house price developments in the overall sample. Instead, subgroups of cities with house price convergence are detected. These convergence clubs are then used to test the influence of fundamental factors on housing prices in light of the spatial utility equilibrium theory. The results show that both GDP per capita growth and population growth have a significantly positive impact on house price convergence levels of a city.

In the next chapter, the results are interpreted in the light of the spatial utility approach. Based on the inferences, recommendations for policies are made.

7 Interpretation of the Analysis

In this chapter, the significant results of the regression analysis are interpreted in light of the spatial utility equilibrium approach to housing prices. Based on the insights that the significant results of the estimation model provide, policy recommendations are presented to connect the research results with possible solutions to challenges that cities face today and will face in the future.

7.1 Revisiting the Spatial Utility Equilibrium Approach

The convergence analysis results show evidence for the existence of multiple house price convergence clubs that are all comprised of metropolitan areas across both sample countries. This implies that the housing markets in both countries show alignments in housing market developments. The findings are especially supported by the fact that both the initially unmerged and also the merged clubs have a quite balanced number of members from each country. The detected convergence clubs build the foundation for testing the role of house price dynamics within the estimation model that is set up in the theoretical framework.

Growth in GDP per capita has the most stable effect on the level of housing price convergence in the model, indicating that changes in wages have a significantly positive relationship to changes in levels of house price convergence. This is strong evidence for the validity of the spatial utility equilibrium theory, as it signifies that housing prices show higher appreciation when wages increase more rapidly. This, in turn means that - holding all other variables equal - the individual utility of residing in a metropolitan area stays roughly at the same level when wages change, as housing prices change accordingly and act as a counterbalance.

The result gains additional weight by the fact that the proxies for socio-economic conditions and amenities, growth in unemployment rate and average rainfall per month, respectively, are insignificant. Obviously, this result should be taken with some caution, as some explanatory variables might be omitted. At least based on the variables used in this study, the results imply that there are no global common factors except population growth that compensate for changes

in housing prices that are not accompanied by changes in GDP per capita.
As already mentioned, this is a striking result. City-specific amenities and socio-economic conditions do not have a globally aligned effect on housing price dynamics, and consequently do not act as a factor in the spatial utility system in an international comparative perspective. While there might exist housing price dynamics that are dependent on amenities within a single country (Kim and Rous, 2012), this relationship breaks down in an international perspective and identifies GDP per capita as a main driver of housing price dynamics.

Population growth is the second variable that has a significantly positive impact on convergence club membership and therefore the level of housing price convergence. This result confirms the findings of multiple other papers (Malpezzi, 1999; Blanco et al., 2016; Holmes et al., 2019). As described in the theoretical framework, the relation of population growth to the level of housing price convergence is used as a proxy for housing supply inelasticity. As population growth significantly increases the probability that a city is a member of a convergence club that convergences to a higher level of housing prices, it is evident that the sample cities have a quite inelastic housing supply. This implies that new construction cannot keep up with the increasing population. Reasons for this might be geographical restrictions or strict building regulations.

The analysis finds evidence for an international relation of house price convergence systems. The house price convergence systems in each country are related by the common positive impact of growth in GDP per capita, which describes a clear influence of wages on house price convergence levels. Furthermore, the positive relation of population growth and house price convergence levels indicate high housing supply inelasticity. The other tested variables were insignificant, which implies that city-specific attributes other than population growth and GDP per capita do not show international alignment in light of the estimation model.
The conclusion is that there is evidence for international alignment of house price convergence systems. Furthermore, there are common fundamental factors that show clear evidence for the validity of the spatial utility equilibrium approach to determine house price dynamics.

7.2 Policy Recommendations

Despite the confident use of GDP per capita as a measure of wages, it ignores the potential effect that an increasing wealth gap (Fredriksen, 2012) has on the utility of individuals. Increasing wealth inequality that occurs alongside increasing GDP per capita and, evidently, house prices, may lead to a situation where some individuals have an utility that is above-average and some below average. As this is a violation of the spatial utility equilibrium, it would potentially lead to a crowding-out effect for the individuals with a below-average utility.
As a consequence of the potential inequality effect, policy makers must aim to reduce overall wealth inequality by appropriate policy measures. Firstly, increases in GDP per capita with accompanying increasing wealth inequality should not affect location decisions of individuals. To achieve this, future policy should keep housing affordable for all citizens of a city. This can be realised by the extension of government social housing programs. Alternatively, real estate investors and landlords can receive subsidies if they invest in or make their property available for social housing initiatives. An example for this can be observed in Hamburg, Germany, where the city government subsidises real estate investors who allocate new construction for social housing (IBF Hamburg, 2019). Despite the option of making housing itself more affordable, policymakers can also aim to reduce overall wealth inequality to align levels of utility. This could be done by, for instance, increasing minimum wages, enhanced social security, and extended wealth transfer through different tax systems.

Additionally, the significantly positive relationship of population growth and house price convergence levels confirms the popular impression of increasing unaffordability of housing in the growing cities of developed countries. The topic gains relevance constantly in light of rapid global urbanisation that is described in this study. Thus, policy must address the issue of housing supply inelasticity and adapt measures that increase the flexibility of housing markets in cities. An attractive idea is the reorganisation of city zones to allow for more residential building construction. To incentivise construction, the government can subsidise real estate investors to build residential property instead of other types of buildings.
Lastly, some big cities with consistently high population growth increasingly adapt policies with the aim of decentralising cities by shifting economic and administrative functions away from the

urban core to surrounding urban areas. A prime example of this are the future development plans of Beijing, which include to shift offices, factories, as well as government institutions to outside urban areas (Roxburgh, 2019). This is supposed to relieve the city from persistent population growth by increasing economic incentives for individuals to move away from the city core. In light of the spatial utility theory, the intention of this policy is to increase wages and improve socio-economic conditions to increase the potential utility that individuals could acquire by moving to outside urban areas.
Another city that follows a similar concept is Seoul, the capital of South Korea. The national government establishes so-called 'New Towns' in regions surrounding the metropolitan area of Seoul (Bae, 2019) with the intention to lower the intense migration pressure on the urban core. While the initiative in Beijing has various goals, the declared aim of the policy in South Korea is quite literally to take away pressure from the intense Seoul housing market. Using policy to control housing prices by increasing the spatial utility elsewhere is an excellent real-life application of the spatial utility equilibrium theory.

On top of that, the Korean land minister, Kim Hyun-Mee, stated that "the job of the ministry and of the government is to establish a country where people may be happy regardless of their residential location" (Bae, 2019), which is a terrific quote that touches upon the very core of the spatial utility equilibrium approach.

8 Conclusion

This thesis delivers pioneering research on house price convergence and its relation to fundamental factors. For the first time, the novel method for convergence detection created by Phillips and Sul (2007) is applied on a sample consisting of cities from multiple countries to find convergence patterns in housing prices that are internationally valid. The acquired evidence for house price convergence in multinational subgroups - convergence clubs - serves as a foundation for an analysis of potential common fundamental factors that determine the membership of a city in a convergence club. This is done by utilising a logistic regression approach that makes it possible to calculate the probability impact that fundamental factors have on the club membership of the sample cities. A major achievement of this study is to derive a direct relation of the spatial utility equilibrium model to the methodology applied in the analysis.

As the application of the convergence algorithm finds distinctive housing price convergence clubs, it supplies clear evidence for an international pattern of house price convergence in developed countries. This confirms the expectation that globally increasing urbanisation as well as internationalisation of markets and people's livelihoods have an aligning effect on the housing markets. Currently, the insight is limited to highly developed countries, as both sample countries are part of the OECD and have a high development status.
Additionally, significant evidence is found for the influence of underlying common factors that affect housing markets in both sample countries. Specifically, it is found that positive growth in GDP per capita in a city, which is used as a proxy for wages, increases the probability of the city to be a member of a convergence club that converges to a higher level of housing prices over time. Furthermore, positive population growth increases the probability of being a member in a convergence club that converges to a higher level of housing prices over time as well, which is evidence for housing supply inelasticity in the city sample.

Despite the relevance of the results, the analysis is subject to some limitations that ought to be resolved in the future. The main issue in this study - but also in research on housing prices in general - is the lack of available data. For this reason, the methodology applied is purposely made fit for an application to an expanded data set as soon as it becomes available in the future. An increased sample size will most likely lead to more robust results and add further validity to the research. As of writing this thesis, the amount of city-specific housing price data is quite underwhelming. Nevertheless, due to rapid global urbanisation and the resulting importance of the topic, international organisation show increased efforts to improve this situation. An example for this is the effort of the OECD (OECD, 2012) and the European Union (Dijkstra and Poelman, 2012) to align definitions and data for metropolitan areas. A sample with cities from more countries would increasingly honour the aim of a global research approach.

While the time frame used in this study supplies a sufficient amount of observations for the convergence analysis, a comparison of different periods could help to compare the impact of systemic factors on the housing market.

The accumulation of international data for fundamental factors poses a challenge in alignment due to differing methodologies and measures from country to country. An enhanced procedure of international data alignment is necessary. Again, international organisations are well-suited for further progress.

In addition to that, there is a need to unwind further details about the behaviour of the fundamental common factors used in this analysis to get a better impression of the effects they have on housing prices as well as individual utilities. For instance, the impact of GDP per capita can be closer examined by adding wealth inequality measures to the model. Related to that, the nature of population growth can be examined in more detail by observing the specifics of migration flows.

Rapid global urbanisation demands global dynamics of housing prices and fundamental factors to be understood. The aspiration of this study and related future studies should be to use the potential of the knowledge acquired to shape solutions for challenges of people living in cities today and in the future.

References

Abraham, J. M. and Hendershott, P. H. (1996). Bubbles in Metropolitan Housing Markets. *Journal of Housing Research*, 7(2):191–207.

Apergis, N. and Payne, J. E. (2012). Convergence in U.S. house prices by state: evidence from the club convergence and clustering procedure. *Letters in Spatial and Resource Sciences*, 5(2):103–111.

Apergis, N., Simo-Kengne, B., and Gupta, R. (2015). The Long-Run Relationship Between Consumption, House Prices, and Stock Prices in South Africa: Evidence from Provincial-level Data. *Journal of Real Estate Literature*, 22(1):83–99.

Austin, P. C. and Steyerberg, E. W. (2017). Events per variable (EPV) and the relative performance of different strategies for estimating the out-of-sample validity of logistic regression models. *Statistical Methods in Medical Research*, 26(2):796–808.

Awaworyi Churchill, S., Inekwe, J., and Ivanovski, K. (2018). House price convergence: Evidence from Australian cities. *Economics Letters*, 170:88–90.

Bae, H. (2019). *Ministry unveils final new town project to add 110,000 homes in Seoul area.* "Retrieved May 10, 2019, from The Korea Herald online: http://www.koreaherald.com/view.php?ud=20190507000661.

Bailey, M. J., Muth, R. F., and Nourse, H. O. (1963). A Regression Method for Real Estate Price Index Construction. *Journal of the American Statistical Association*, 58(304):933.

Bartkowska, M. and Riedl, A. (2012). Regional convergence clubs in Europe: Identification and conditioning factors. *Economic Modelling*, 29(1):22–31.

Blanco, F., Martín, V., and Vazquez, G. (2016). Regional house price convergence in Spain during the housing boom. *Urban Studies*, 53(4):775–798.

Capozza, D. R., Hendershott, P. H., and Mack, C. (2004). An Anatomy of Price Dynamics in Illiquid Markets: Analysis and Evidence from Local Housing Markets. *Real Estate Economics*, 32(1):1–32.

Case, K. E. and Shiller, R. J. (1987). Prices of Single Family Homes Since 1970: New Indexes for Four Cities. Technical Report 2393, National Bureau of Economic Research, Cambridge, MA.

Case, K. E. and Shiller, R. J. (1989). The Efficiency of the Market for Single-Family Homes. *The American Economic Review*, 79(1):125–137.

Case, K. E. and Shiller, R. J. (1990). Forecasting Prices and Excess Returns in the Housing Market. *Real Estate Economics*, 18(3):253–273.

Clapp, J. M. and Giaccotto, C. (1998). Residential Hedonic Models: A Rational Expectations Approach to Age Effects. *Journal of Urban Economics*, 44(3):415–437.

Clark, S. P. and Coggin, T. D. (2009a). Trends, cycles and convergence in U.S. regional house prices. *Journal of Real Estate Finance and Economics*, 39(3):264–283.

Clark, S. P. and Coggin, T. D. (2009b). Trends, Cycles and Convergence in U.S. Regional House Prices. *The Journal of Real Estate Finance and Economics*, 39(3):264–283.

Cook, S. (2003). The convergence of regional house prices in the UK. *Urban Studies*, 40(11):2285–2294.

Cook, S. (2005). Detecting long-run relationships in regional house prices in the UK. *International Review of Applied Economics*, 19(1):107–118.

Demir, C. and Yildrim, M. O. (2017). Convergence in house prices across OECD countries : A panel data analysis. *Ekonomická revue – Central European Review of Economic Issues*, 20(March):5–15.

Dijkstra, L. and Poelman, H. (2012). Cities in Europe - The new OECD-EC definition - Regional Policy - European Commission. Technical report, European Comission.

EIA (2019). *International Energy Statistics*. "Retrieved April 28, 2019, from U.S. Energy Information Administration online: https://www.eia.gov/beta/international/data/browser.

Englund, P. and Ioannides, Y. M. (1997). House Price Dynamics: An International Empirical Perspective. *Journal of Housing Economics*, 6(2):119–136.

Fisher, A. G. B. (1939). Production, Primary, Secondary and Tertiary. *Economic Record*, 15(1):24–38.

Flavin, M. and Yamashita, T. (1998). Owner-Occupied Housing and the Composition of the Household Portfolio Over the Life-Cycle. Technical report, National Bureau of Economic Research, Cambridge, MA.

Fredriksen, K. B. (2012). Income Inequality in the European Union. *OECD Economics Department Working Papers*, (952).

Gatzlaff, D. H. and Haurin, D. R. (1998). Sample Selection and Biases in Local House Value Indices. *Journal of Urban Economics*, 43(2):199–222.

Glaeser, E. L. and Gyourko, J. (2007). Housing Dynamics. Technical Report National Bureau of Economic Research, National Bureau of Economic Research, Cambridge, MA.

Glaeser, E. L., Gyourko, J., Morales, E., and Nathanson, C. G. (2014). Housing dynamics: An urban approach. *Journal of Urban Economics*, 81(1):45–56.

Glaeser, E. L., Gyourko, J., and Saks, R. E. (2006). Urban growth and housing supply. *Journal of Economic Geography*, 6(1):71–89.

Gupta, R., Miller, S. M., and van Wyk, D. (2010). Financial Market Liberalization, Monetary Policy, and Housing Price Dynamic. *SSRN Electronic Journal*, 11(1).

Gyourko, J., Mayer, C., and Sinai, T. (2013). Superstar cities. *American Economic Journal: Economic Policy*, 5(4):167–199.

Gyourko, J. and Voith, R. (1992). Local market and national components in house price appreciation. *Journal of Urban Economics*, 32(1):52–69.

Hiebert, P. and Roma, M. (2010). Relative house price dynamics across euro area and US cities Convergence or divergence? (1206).

Holmes, M. J. (2007). How convergent are regional house prices in the United Kingdom? Some new evidence from panel data unit root testing. *Journal of Economic and Social Research*, 9(1):1–17.

Holmes, M. J. and Grimes, A. (2008). Is There Long-run Convergence among Regional House Prices in the UK? *Urban Studies*, 45(8):1531–1544.

Holmes, M. J., Otero, J., and Panagiotidis, T. (2019). Property heterogeneity and convergence club formation among local house prices. *Journal of Housing Economics*, 43:1–13.

IBF Hamburg (2019). *Wohnraumförderprogramm des Senats*. Retrieved April 13, 2019, from Stadt Hamburg online: https://www.hamburg.de/bsw/wohnungsbaufoerderung/.

Jong, V. M. d., Eijkemans, M. J., van Calster, B., Timmerman, D., Moons, K. G., Steyerberg, E. W., and van Smeden, M. (2019). Sample size considerations and predictive performance of multinomial logistic prediction models.

Jud, D. G. and Winkler, D. T. (2002). The Dynamics of Metropolitan Housing Prices. *The Journal of Real Estate Research*, 23(1-22):29–46.

Kelly, J.-F., O'Toole, M., Oberklaid, M., and Hunter, J. (2013). *Productive Cities : Opportunity in a Changing Economy*. Number 2013-5. Grattan Institute.

Kim, Y. S. and Rous, J. J. (2012). House price convergence: Evidence from US state and metropolitan area panels. *Journal of Housing Economics*, 21(2):169–186.

Klein Goldewijk, K., Beusen, A., Van Drecht, G., and De Vos, M. (2011). The HYDE 3.1 spatially explicit database of human-induced global land-use change over the past 12,000 years. *Global Ecology and Biogeography*, 20(1):73–86.

MacDonald, R. and Taylor, M. P. (1993). Regional House Prices in Britain: Long-Run Relationships and Short-Run Dynamics. *Scottish Journal of Political Economy*, 40(1):43–55.

MacGee, J. (2009). Why Didn't Canada's Housing Market Go Bust? *Economic Commentary*, (September 2009).

Malpezzi, S. (1999). A Simple Error Correction Model of House Prices. *Journal of Housing Economics*, 8(1):27–62.

Meen, G. (1999). Regional House Prices and the Ripple Effect: A New Interpretation. *Housing Studies*, 14(6):733–753.

Meen, G. (2002). The time-series behavior of house prices: A transatlantic divide? *Journal of Housing Economics*, 11(1):1–23.

Mikhed, V. and Zemčík, P. (2009). Testing for Bubbles in Housing Markets: A Panel Data Approach. *The Journal of Real Estate Finance and Economics*, 38(4):366–386.

Muellbauer, J. and Murphy, A. (1997). Booms and Busts in the UK Housing Market. *The Economic Journal*, 107(445):1701–1727.

NRC (2014). *Oil Resources*. "Retrieved April 29, 2019, National Resources Canada online: https://www.nrcan.gc.ca/energy/oil-sands/18085.

OECD (2012). Redefining "Urban": A New Way to Measure Metropolitan Areas. Technical report, Paris.

OECD (2013). *Definition of Functional Urban Areas (FUA) for the OECD Metropolitan Database.* "Retrieved February 10, 2019, from U.S. Energy Information Administration online: https://www.oecd.org/cfe/regional-policy/.

OECD (2019). *House Prices.* "Retrieved January 28, 2019, from OECD online: https://stats.oecd.org/.

Phillips, P. C. B. and Sul, D. (2007). Transition Modeling and Econometric Convergence Tests. *Econometrica*, 75(6):1771–1855.

Phillips, P. C. B. and Sul, D. (2009). Economic transition and growth. *Journal of Applied Econometrics*, 24(7):1153–1185.

Poterba, J. M. (1984). Tax Subsidies to Owner-Occupied Housing: An Asset-Market Approach. *The Quarterly Journal of Economics*, 99(4):729–752.

Poterba, J. M., Weil, D. N., and Shiller, R. J. (1991). House Price Dynamics: The Role of Tax Policy and Demography. *Brookings Papers on Economic Activity*, 1991(2):143.

Rherrad, I., Mokengoy, M., and Kuate Fotue, L. (2019). Is the Canadian housing market 'really' exuberant? Evidence from Vancouver, Toronto and Montreal. *Applied Economics Letters*, pages 1–6.

Roback, J. (1982). Wages, Rents, and the Quality of Life. *The Journal of Political Economy*, 90(6):1257–1278.

Rosen, S. (1979). Wage-based indexes of urban quality of life. In *Miezkowski. P., Straszheim, M. (Eds.), Current Issues in Urban Economics*, pages 74–104. North-Holland.

Roxburgh, H. (2019). *China's radical plan to limit the populations of Beijing and Shanghai.* Retrieved May 10, 2019, from Guardian online: https://www.theguardian.com/cities/2018/mar/19/plan-big-city-disease-populations-fall-beijing-shanghai.

Saiz, A. (2010). The Geographic Determinants of Housing Supply. *Quarterly Journal of Economics*, 125(3):1253–1296.

Tsai, I.-C. (2018). House price convergence in euro zone and non-euro zone countries. *Economic Systems*, 42(2):269–281.

UN (2018). 2018 Revision of World Urbanization Prospects. *United Nations Department of Economic and Social Affairs.*

Van Smeden, M., De Groot, J. A., Moons, K. G., Collins, G. S., Altman, D. G., Eijkemans, M. J., and Reitsma, J. B. (2016). No rationale for 1 variable per 10 events criterion for binary logistic regression analysis. *BMC Medical Research Methodology*, 16(1):1–12.

Vittinghoff, E. and McCulloch, C. E. (2007). Relaxing the rule of ten events per variable in logistic and cox regression. *American Journal of Epidemiology*, 165(6):710–718.

Wachter, S. (2015). The Housing and Credit Bubbles in the United States and Europe: A Comparison. *Journal of Money, Credit and Banking*, 47(S1):37–42.

Wooldridge, J. M. (2016). *Introductory Econometrics: A Modern Approach.* Nelson Education.

Wooldrige, J. M. (2011). *Econometric Analysis of Cross Section and Panel Data*, volume 7. The MIT Press.

Zabel, J. E. (2004). The demand for housing services. *Journal of Housing Economics*, 13(1):16–35.