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MODELS FOR SPATIAL CONSEQUENCES OF CHANGES IN COMMUTING PATTERNS

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PhD
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Acknowledgements

Moving from Iran, where women are deprived of many human rights, to Norway, a country where women's well-being seems to be prioritized, was a rewarding yet challenging journey. This change allowed me to see how life could have been different for me. I have to admit that as a person with anxiety, adapting to such a significant life change while pursuing a PhD was not easy. The global pandemic and ensuing lockdowns only added to the challenges I faced. It intensified my anxiety, leaving me in a frozen state, overwhelmed by bad memories and nightmares. I did not even want to interact with others anymore. I am grateful to Kristin, the head of the department's administration, who helped me to get back in touch with my supervisor, Jan Ubøe. Fortunately, Jan not only guided me academically but also provided me with essential support, just like a therapist would. Then meeting my boyfriend, Kristian, a sweet and kind person, was the turning point that pulled me back to the world. Even so, it took me several months to gradually overcome the nightmares.

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Contents

Summary of the thesis "Models for Spatial Consequences of Changes in Commuting Patterns"

Provided here is a brief overview of the different parts of the thesis, which consists of four separate papers all related to modeling of journey to work.

Paper1 Land use and transportation interaction modelling frameworks

The paper reviews land-use/transport interaction models (LUTI) and their evolution over the past six decades. The review explores the different modeling frameworks and methodologies applied in LUTI modeling over the years. The categorization proposed by Iacono (2008) is adopted to classify LUTI models into three categories: spatial interaction/gravity-based modeling, econometric modeling, and microsimulation/other computer-based modeling. Spatial interaction/gravity models referred to as "Large-scale" models, emerged by combining the Lowry and four-step models. These models commonly analyze spatial interactions and gravity in transportation flows. Econometric models, the second category of LUTI models, incorporate microeconomic theories such as bid-rent theory and random utility theory to enhance the price mechanism in urban formation. Based on a general equilibrium framework, some of these models expand on computable general equilibrium (CGE) models initially developed for analyzing urban space formation. In the early 1990s, the emergence of the New Economic Geography (NEG) theory significantly impacted spatial economics. The theory emphasizes increasing returns to scale and transportation costs as explanations for forming large agglomerations. Building upon Krugman's work (1991), researchers developed multiregional input-output models referred to as Spatial Computable General Equilibrium (SCGE) models, incorporating characteristics of the NEG theory. In the early 1990s, microsimulation models for transportation and land use emerged, including agent-based, cell-based, and multi-agent models. In the 2000s, researchers developed comprehensive urban microsimulation models capable of capturing population dynamics and the urban environment. One notable model serving as a foundation for this work is the spatial equilibrium model formulated by McArthur (2014). This model aimed to balance large-scale models and SCGE models by incorporating intraregional commuting and shopping patterns typically associated with large-scale models.

Paper 2 An agent-based approach to study spatial structure effects on estimated distance deterrence in commuting.

The paper presents an experimental design to examine spatial structure's impact on estimates of the distance deterrence parameter in a doubly-constrained gravity model. The design utilizes an agent-based simulation framework that considers both commuting and migration responses to changes in spatial structure, considering labor and housing market factors. The agent-based experiments generated a population similar to the demographics of Norway. Each agent is equipped with a utility function and seeks to maximize their utility by considering their net wage after commuting costs and the value of their house. By employing this experimental design, we provide a consistent approach to interpreting the distance deterrence parameter in a spatial interaction model and assessing the stability of parameter estimates across different controlled experiments. We investigate how estimates of the distance deterrence parameter vary based on various spatial structure characteristics. Specifically, we analyze the impact of the central business district's location, clustering of local and basic sector jobs, changes in the road transportation network, and the compactness of the towns within the geography. The main contribution of the paper lies in demonstrating how these parameter estimates are influenced by spatial structure characteristics. The experiments presented in this paper have demonstrated that different spatial structure characteristics should be explicitly accounted for to obtain reliable and unbiased estimates of the distance deterrence parameter in spatial labor market interaction. The results provide a useful guideline for evaluating results in empirical studies, particularly in the context of interregional comparisons of commuting behavior and procedures related to predicting induced commuting and willingness to pay for investments in transportation infrastructure.

Paper 3 An experimental approach to study how commuting behavior reflects preferences, labor market conditions, and housing prices.

This paper employs an agent-based approach to generate spatial interaction data resembling the demographic characteristics of the Norwegian population. The study investigates how a standard spatial interaction model replicates observed trip distribution patterns by conducting controlled experiments. The research explores the influence of labor and housing market conditions on trip distribution and examines the impact on estimates of the distance deterrence parameter. Additionally, the paper addresses the identification of how travel demand is affected by household preferences and budget constraints, utilizing the agent-based approach to differentiate between preference-based and budget-related effects. The decisions regarding travel behavior are influenced by labor and housing market conditions through budgetary considerations. The experimental design focuses on capturing how the estimates of the distance deterrence parameter in commuting reflect various aspects of the labor market, the housing market, and underlying preferences. The findings contribute to both modifications of the standard spatial interaction model and an enhanced understanding of the interpretation of the distance deterrence parameter. The experiments, for instance, reveal a consistent trend: when there are substantial wage disparities but minimal variations in housing prices across towns, the estimated distance deterrence parameter tends to be low. It is important to note that these outcomes result from intricate interactions. Consequently, the analysis highlights the significance of simultaneously considering shopping, moving, and commuting decisions.

Paper 4 Predicting induced commuting from a new fixed link in the transportation network.

In this paper, we study to what degree a standard spatial interaction model represents a reliable approach to predicting induced commuting from investments in the road transportation network. The analysis is derived from agent-based data generation, supplemented by observations from a Norwegian labor market area. The results demonstrate that striving for a model specification with the highest possible explanatory power only sometimes leads to the most accurate predictions. Ignoring relevant information on spatial disparities in wages and housing prices and failing to account for relocation effects introduce a potentially serious bias in predicting commuting induced by a new fixed link. The prediction bias depends on the time perspective. The wider local impacts may lead to substantial under-predictions of induced commuting and the willingness to pay for a new fixed link. Spatial interaction models should, in particular, be used with care in cases where the investments lead to substantial improvements in the labor market accessibility of a previously rural area. In such cases, a cost-benefit assessment should be based on a general spatial equilibrium modeling framework to avoid that induced demand being under-predicted, calling for expensive capacity expansions of the road network.

Land use and transportation interaction modelling frameworks

Azam Azad Gholami

Abstract

This paper presents a review of integrated land-use/transport models (LUTI) over the past six decades. The categorization proposed by Iacono et al. [2008] is adopted to classify LUTI models based on their evolution over time. LUTI models fall into three main categories: spatial interaction/gravity-based modeling, econometric modeling, and microsimulation/other computer-based modeling. The first category, spatial interaction/gravity-based modeling, has adopted similar structures to its origins traced back to Lowry's model (Lowry [1964]). However, in the early to mid-1980s, these models began to be gradually replaced by a new type of modeling known as econometric models. Econometric models expanded upon the understanding of urban formation by incorporating microeconomic theories such as bid-rent theory (Alonso [1964]) and random utility theory (McFadden [1977]) into their frameworks. The development of microsimulation models, commonly referred to as "microsimulation", commenced in the early 1990s. Within the domain of microsimulation, several types of models emerged, including agent-based models, cell-based models for land use change, and multi-agent models for urban modeling.

1 Introduction

Large infrastructure investment projects like transportation often generate considerable public debate between professionals and less professional actors. The costs and benefits of a proposed project have been almost always a controversial subject, between those in favor of the project believing the costs are overestimated, and the benefits are underestimated, and the other way around for those opposing the project (Flyvbjerg [2008], Zhang et al. [2020], Hansen and Ivanova [2012]). Until the twenty-first century, transportation economics primarily relied on the constrictive traditional cost-benefit approach as the other computations were extremely costly. The traditional cost-benefit appraisal of a new road project involves measuring the benefits of the road by calculating the consumer surplus users gain from the reduction in generalized costs. It then deducts the construction costs in market values, as well as the net increase of technological external costs caused by both existing and induced traffic. In other words, it evaluates whether the benefits of the road outweigh its costs in economic terms (Bröcker and Mercenier [2011]).

This approach relies on three conditions: markets must be perfectly competitive, welfare distribution is not a concern, and negative technological externalities outside the transport sector are negligible (Bröcker and Mercenier [2011]). And we know from economic theory that when there is a reasonable degree of perfect competition, only the benefits obtained by infrastructure users in the primary market should constitute the net benefits in a Cost-Benefit Analysis (CBA) (Hansen and Ivanova [2012], Kanemoto and Mera [1985], Jara-Diaz [1986]). This implies that other indirect or subsequent benefits may not be considered as they are already reflected in the primary market benefits.

To clarify, irrespective of the market structure within the transportation sector, market imperfections in the transportation-using sectors (secondary markets) will introduce scale effects into the impact analysis which are not existent in a traditional perfect competition framework (Bröcker and Mercenier [2011], Hansen and Ivanova [2012]). Cost reductions result in an expansion of production, leading producers to move down the average cost curve. This, in turn, gives rise to effects that are referred to as wider economic effects of transport cost reductions, as identified in the (SACTRA [1999]) report. In a perfect competition framework without externalities, such effects are nonexistent, as the economic welfare gain resulting from a marginal transport cost reduction is equivalent to the reduction in cost and nothing more. However, the situation is different in economies of scale, as the marginal welfare gain tends to exceed the marginal cost reduction (Bröcker and Mercenier [2011], Vickerman [2008]). So, taking only the direct effects of a project into account, or in other words, using the traditional cost-benefit approach, may cause an over- or underestimation of the total project-specific benefits (Harberger [1964], SACTRA [1999]), which in turn may result in suboptimal public investment strategies (Hansen and Johansen [2017]).

Another type of effect often neglected in the assessment of transportation projects, which we have focused on is relocation effects. Relocation effects represent the basic component of what Welde and Tveter [2022] refer to as wider local impacts. Welde and Tveter [2022] define wider local impacts as the second-order effects that transportation projects have on communities, while they discuss wider economic impacts as the third-order effects of transportation projects.

The traditional cost-benefit analysis used for investments in transportation infrastructure fails to consider the effects of relocation because it is built upon models that assume a fixed location pattern of jobs and workers. While this may be reasonable in the short term, it is only sometimes the case in the long term. Over time, firms and workers should be expected to respond to the changes in spatial interaction by relocating to areas that offer better opportunities for profit and residential location preferences. Hence, a response in location choices should be expected due to a new road. Then again, in the long term, firms and workers take advantage of the newly available combinations of jobs and residential locations. This is probably an important part of the explanation for prediction errors in calculating induced traffic and welfare benefits in traditional cost-benefit appraisals of investments in road transportation infrastructure. In addition, predictions of how the location pattern is affected are important for regional policy. For example, whether the investment encourages a more decentralized location pattern or contributes to centralization and urbanization. Also if such effects are compatible with ambitions of sustainable development of the economy.

McArthur et al. [2020] highlights two key factors that influence the magnitude and direction of the error that might occur in case of ignoring the relocation effect: the sensitivity of people's migration decisions to distance and the spatial structure of the region. When workers are sensitive to distance and the change in infrastructure is close to the CBD, the errors can be significant. Neglecting these effects can result in incorrect predictions of travel demand and environmental costs, potentially leading to decisions that are suboptimal in terms of equity and economic efficiency (McArthur et al. [2020]).

Therefore, it is argued that a more comprehensive economic analysis framework may be needed to address these limitations of the traditional cost-benefit analysis approach. A framework which is integrating transport with the land use perspective. There are, however, several such models in the literature, which we discuss later in this paper. The following are the most common scientific methods for estimating the effects of infrastructure investments that can be found in the literature (Oosterhaven et al. [2001], Tavasszy et al. [2002], Hansen and Ivanova [2012]):

Micro surveys with firms
Estimation of quasi production functions
Partial equilibrium potential models
Macro and regional economic models
Land-Use Transportation Interaction (LUTI) models

Spatially detailed models like LUTI models are considered to be the tools frequently used for simulating the effects of significant infrastructure investments (Hansen and Ivanova [2012], Hansen and Johansen [2017]).

This literature review paper is organized as follows. Section 2 provides a brief history of the development of LUTI models over time and the categories into which they are divided in the literature. Also, the general structure of LUTI models is discussed, focusing on UrbanSim, which is recognized as the most widely used LUTI model. In Section 3, SCGE models are reviewed in addition to the modeling framework of an SCGE model. Section 4 reviews a spatial equilibrium model formulated by McArthur et al. [2014]. Finally, in section 5, the agent-based microsimulation model that we developed is compared with the other models, with a particular focus on McArthur et al. [2010, 2014]'s model, which served as the fundamental basis for our approach.

2 Land Use Transportation Interaction Models (LUTI)

Land Use and Transportation Interaction Models (LUTI) are powerful tools for studying how land use and transportation systems interact to shape the spatial patterns of human activity in urban and regional contexts. The basic idea behind these models is that land use and transportation are fundamentally linked (Hansen [1959], Wegener [2004]). The interdependence between land use and transportation has given rise to the concept of the "land-use transport feedback cycle". The "land-use transport feedback cycle" (Kelly [1994], Wegener and Fürst [1999]) suggests that changes in land use can affect transportation demand, which in turn can affect accessibility and the spatial distribution of land uses. This cyclical process can lead to a self-reinforcing feedback loop, ultimately resulting in a complex and dynamic urban system.

Land use and transportation modeling history can be traced back to the late 1950s (Batty [1979]), but the first operational LUTI model was built in the early 1960s. Iacono et al. [2008] has proposed three categories to classify LUTI models based on their evolution over time (see figure 1). The categories are: spatial interaction/gravity-based modeling, econometric modeling, and microsimulation/other computer-based modeling. Lowry's model (Lowry [1964] initiated the first category of models based on theories of spatial interaction, including the gravity model that was popular in quantitative geography at the time. Many of these models have similar structures to Lowry's model (Iacono et al. [2008]). A thorough review of this model and its variations is presented in the work by Horowitz [2004]. According to Iacono et al. [2008], models based on spatial interaction frameworks were gradually replaced by models grounded in random utility theory and econometric methods from the early to mid-1980s.

The development of transportation and land use models known as "microsimulation" started in the early 1990s. During this time, significant advancements in computational power facilitated the operation of these models. The various types of microsimulation models that emerged included agent-based models, cell-based models for land use change, and multi-agent models for urban modeling. In the early 2000s, researchers started focusing on creating comprehensive urban microsimulation models that captured the dynamics of population changes and the urban environment. These models aimed to simulate the choices made by individuals within the urban setting, considering the evolving nature of the population and the urban environment itself. In the following, further information regarding each category will be provided.

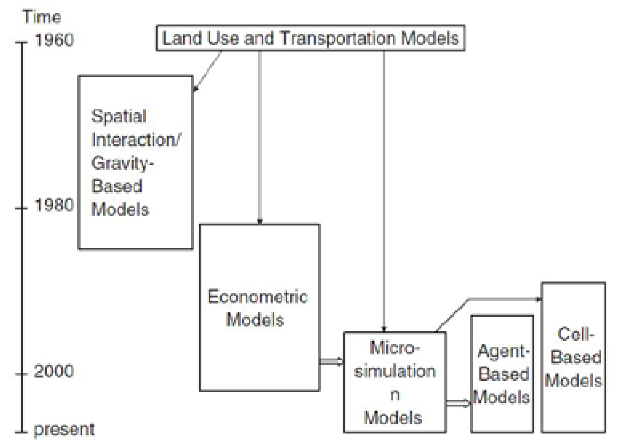

Figure 1: The evolutionary progression of Land Use and Transportation Models over time (adapted from Iacono et al. [2008])

2.1 Spatial Interaction Models

The earliest land use and transportation models are based on the spatial interaction framework. While there were many different formulations of spatial interaction models, most of them mainly centered their evaluation on the gravity model (Iacono et al. [2008]).

In gravity models of trip distribution problems, spatial interaction is explained by three main factors: the distance between an origin and a destination, the generativity of origins, and the attraction of destinations. For commuting, the generativity of origins is generally defined in terms of the number of workers residing in the zone. At the same time, the attraction of a destination is measured by the local number of jobs (see Sen and Smith [2012]). A standard formulation of a doubly constrained gravity model is:

$$T_{ij} = A_i O_i B_j D_j \exp(-\beta d_{ij})$$

$$A_i = \left[\sum_j B_j D_j \exp(-\beta d_{ij}) \right]^{-1}$$

$$B_j = \left[\sum_i A_i O_i \exp(-\beta d_{ij}) \right]^{-1}$$

where:

T_{ij} is the estimated number of commuters from origin i to destination j, $i, j = 1, ..., n$

O_i is the observed number of trips originating from zone $i = 1, ..., n$

D_j is the observed number of trips destined for zone $j = 1, ..., n$

d_{ij} is travelling time by car, from origin i to destination j; $i, j = 1, ..., n$

β is a distance deterrence parameter. A_i and B_j are the balancing factors that ensure the fulfillment of the marginal total constraints for this trip distribution problem; $\sum_j T_{ij} = O_i$ and $\sum_i T_{ij} = D_j$.

The standard doubly-constrained gravity model is valuable for appraising transportation investment projects. The basis for determining the benefits in a cost-benefit analysis is traffic, and a doubly-constrained gravity model as a pure trip distribution model can work correctly for this purpose. However, the issue is that transportation investments have impacts beyond just traffic, affecting the land-use decisions made by households and firms over the long term, which in turn can impact traffic patterns. Moreover, the gravity model's static nature assumes that existing land-use patterns served by existing transportation will be maintained in the future, including prices, qualities, and service levels (Lee Jr [1973]). This assumption can lead the model to be biased in estimating the effects of infrastructure investment. Additionally, the model is valid at the metropolitan scale but may not have explanatory power at the neighborhood level due to the ecological fallacy of attributing individual behavior from aggregate relationships (Lee Jr [1973]).

Spatial Interaction/Gravity models were initially developed by combining the Lowry model (Lowry [1964]) and the four-step model (Mitchell and Rapkin [1954]). The model called ITLUP (Integrated Transportation and Land Use Package) developed by (Putman [1974]) is considered the first LUTI package. Other models like Leeds Integrated Land Use (LILT) (Mackett [1983]), CALUTAS (Nakamura and Hayashi [1981], Nakamura et al. [1983]), DORTMUND (Wegener [1985]), AMERSFOORT (Floor and De Jong [1981]), MEP (Geraldes et al. [1978]), and OSAKA (Amano et al. [1983]) also belong to this category as they employed gravity models to allocate land use distribution (Kii et al. [2016]).

Some models incorporated elements of econometric theory into the system to some extent. They used concepts like utility maximization and market equilibrium techniques to evaluate land use's economic impact and efficiency. For instance, the Technique for the Optimal Placement of Activities in Zones (TOPAZ) (Brotchie et al. [1980]) and SALOC models (Lundqvist [1984]) employed a cost minimization framework to allocate activities to different zones. TOPAZ also included predictive mechanisms within the system by considering accessibility in a gravity model (Kii et al. [2016]).

The first category of LUTI models was characterized by their large and complicated nature, which made them opaque to decision-makers. So, these Large-scale models were only applied to a limited number of specific urban areas and did not gain widespread usage, compared to more partial models such as the four-step transportation model (Webster et al. [1988], Kii et al. [2016]). These models were referred to as "Large-scale"in the literature (Lee Jr [1973], Boyce [1988], Lee [1994]).

One drawback of these models was that they did not incorporate the explicitly priced land or floor market into their representation (Kii et al. [2016]). While some models incorporated pricing mechanisms, their approach to doing so was somewhat ad hoc in manner. Recognizing this limitation, Lee Jr [1973], for instance, identified several flaws in these large-scale urban models, including their hyper-comprehensiveness, grossness, hungriness, wrongheadedness, complicatedness, mechanicalness, and expensiveness (see Lee Jr [1973]). These flaws highlight the gap between large-scale models and their intended users, urban planners, and policymakers (Te Brömmelstroet et al. [2014]). Additionally, Batty [1979] suggests that the failure of urban models was due to their immaturity as a science, resulting from the lack of sufficient theoretical foundations.

The criticisms of the models prompted the emergence of theories relative to urban models. In response, the International Study Group on Land-Use/ Transportation Interaction (ISGLUTI 1981-1991) was established to assess the performance of LUTI models using a standardized testing procedure. The study conducted by ISGLUTI yielded two main findings. Firstly, while there is a general alignment among models regarding the direction and magnitude of policy impacts, the level of agreement decreases as the models' parameters become more detailed or disaggregated. Secondly, the study suggested that a proper pricing mechanism is preferable over a set of rules for representing transferable locational preferences. These findings played a significant role in guiding the development of next-generation LUTI models (Kii et al. [2016]).

2.2 Econometric Models

In keeping with the results of the ISGLUTI study, the second generation/category of LUTI models, referred to as Econometric models by Iacono et al. [2008], has further elaborated the price mechanism in urban formation. This is achieved by incorporating microeconomic theories such as bid-rent theory (Alonso [1964]) and random utility theory (McFadden [1977]) into the models. Examples of such LUTI models include MUSSA (Martinez [1996]), RURBAN (Miyamoto and Kitazume [1989]), and STASA (Haag [1990]), which combined these two theoretical frameworks to model the location choices made by residents and enterprises in urban areas.

IRPUD was developed by (Wegener [1982]), a comprehensive land-use transport model focusing on individual households and their location choices. Unlike conventional models, the IRPUD model challenges the notion of reaching an equilibrium in land-use simulation periods. It recognizes that equilibrium is only sometimes achieved due to a dynamic environment and slow response times of various stakeholders such as households, businesses, developers, and planners. The model considers the price of new dwellings and commuting distance to the main workplace as significant constraints in determining location choices (Moeckel et al. [2018]). The Metroscope model (Conder and Lawton [2002]) developed for Portland, Oregon, examines the costs associated with housing, transportation, food, health, and other expenses to ensure that household budgets are not surpassed. PECAS (Hunt and Abraham [2003]) is another land-use model focusing on achieving an equilibrium between competing demands for developable land. It considers available floor space, prices, accessibility, and other location factors to determine household relocations. PECAS combines the bid-rent approach into a spatial economic model with a microscopic land development model. DELTA (Simmonds and Still [1999]), TIGRIS XL (Zondag et al. [2015]), MEPLAN (Echenique et al. [1990], Echenique [2004]) and TRANUS (De la Barra [1989]), PECAS (Hunt and Abraham [2005]), (CATLAS) (Anas [1982]), METROSIM (Anas and Arnott [1994]), RELU-TRAN (Anas and Liu [2007]) are examples of this category of LUTI models (Kii et al. [2016], Moeckel et al. [2018]). The works by Anas and associates are built upon a general equilibrium framework, allowing for the calculation of precise economic benefits. These models are considered an extension of computable general equilibrium (CGE) models (Taylor and Black [1974]), initially created to analyse urban space formation.

To summarize, the econometric models successfully incorporated behavioral theory into urban modeling, which was disregarded in the first category of LUTI models. This incorporation led to a more robust theoretical foundation for urban models, and the adaptable nature of the theory allowed for the inclusion of diverse factors relative to urban activities (Kii et al. [2016], Bierlaire et al. [2015]).

2.3 Microsimulation and the other computer-based models

In the 1960s, (Orcutt [1961]) suggested the concept of microsimulation, which involves simulating individuals instead of modeling the population as a whole (Moeckel et al. [2018]). The microsimulation model usually employs an agent-based approach in which the behavior of disaggregated agents, such as individuals, households, and firms, is simulated within the limits of time and space (Kii et al. [2016]). However, it was not until the 1990s that the adoption of activity-based models in transportation was prompted by emerging social changes, including the development of information communication technologies (ICTs), increasing environmental concerns, socio-demographic changes (Ben-Akivai et al. [1996], Kitamura et al. [1996]), and the associated travel demands of individuals and households (Buliung and Kanaroglou [2007]).

Information technology (IT) advancement allowed individuals to alter their activity patterns by changing the timing and resources they previously used for travel. As environmental planning in transportation became more important, there was a need for diverse and dynamic instruments of travel demand management. Additionally, socio-demographic changes such as an aging population, an increasing female workforce, and changing household structures significantly affected travel demand. Activity-based models with a high spatiotemporal degree were developed to incorporate the influence of these social changes. These models considered activity substitution between in-home and out-of-home activities and activity scheduling that allocated time for travel to different activities (Kii et al. [2016]).

The need for changes in transportation models also affected urban models. Wegener's work (Wegener [2004]) highlighted the challenge of introducing activity-based models in urban modeling. Individual and household travel decisions are influenced by spatial and temporal constraints within a diverse urban landscape. A single global model would not adequately capture the local variations in relationships between activities, travel outcomes (such as activity duration, frequency, and mode), and common factors related to income, mobility, and urban form (Buliung and Kanaroglou [2007]). Therefore, efforts were made to develop microsimulation models with a higher spatiotemporal degree of land-use transportation interaction in the 2000s (Moekel et al. [2003], Salvini and Miller [2005]).

Accessibility analysis also emerged as a challenge for transportation policy, as it indicates the interaction between land use and transportation. Developing a new accessibility indicator in activity-based models required significant efforts, as these models are based on inhabitants' utility (Geurs and Van Wee [2004]). Dong et al. [2006] proposed activity-based accessibility indicators that could be estimated based on individuals' travel behavior and personal utility. In the pursuit of more comprehensive models, an agent-based demand modeling framework for large-scale microsimulations was presented by (Balmer et al. [2006]). This framework utilized simple algorithms with the potential for further improvement to validate the resulting demand. Furthermore, the advantages of activity-based models over trip-based models were discussed by (Shiftan [2008]), particularly in understanding travelers' responses to specific land-use policies like bicycle path provision, local shops, safety improvements, and school quality. ILUTE (Salvini and Miller [2005], Farooq and Miller [2012]) and ILUMASS (Moekel et al. [2003], Strauch et al. [2004]) are examples of comprehensive microsimulation models that employ this agent-based approach. The first successful integration of microsimulation land-use and transport models was achieved by (Waddell et al. [2010]) in their work for San Francisco (Moeckel et al. [2018]).

2.4 General structure of LUTI models

Most operational LUTI models consist of three primary sub-model components: land use, socio-demographic, and transportation. The sub-models may either be tightly integrated or loosely connected to establish input-output relationships during the execution of the model (Acheampong and Silva [2015]). See Figure 2 .

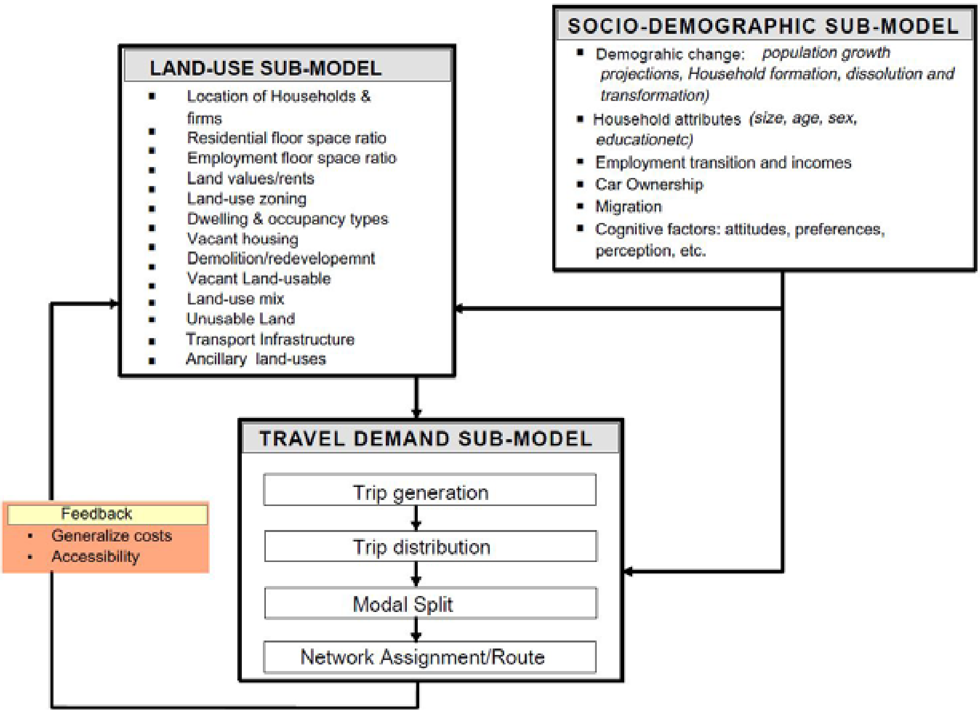

Figure 2: Generalized structure of an operational LUTI model (adapted from Acheampong and Silva [2015])

The socio-demographic sub-model includes socioeconomic variables that influence households' location selection and travel behavior. The level of detail captured in socio-demographic factors and processes varies among model platforms. For example, DELTA-START (Simmonds and Still [1999], Simmonds [2001]) and UrbanSim (Waddell [2000]) have detailed demographic transition sub-models that simulate the dynamics of household formation, dissolutions, and transformations, as well as employment transition models that simulate job creation and removal. In most LUTI modeling frameworks, such as LILT (Mackett [1983, 1990, 1991]), MUSSA–ESTRAUS (Martinez [1992, 1996]) and RAMBLAS (Veldhuisen et al. [2000]), the demographic sub-models typically categorize households into segments consisting of socioeconomic groups that share similarities. Some operational models for instance DELTA-START and IRPUD (Wegener [1982, 1996, 2004]) also include migration processes as part of their socio-demographic sub-models (Acheampong and Silva [2015]).

The land-use sub-model typically contains valuable information about the urban land market, such as residential and employment space ratios, land values, dwelling and occupancy types, land-use mix, housing vacancy, demolition, and redevelopment. According to (Acheampong and Silva [2015]) most existing models such as IMREL, KIM, MEPLAN, TRESIS, METROSIM, MUSSA, PECAS, RURBAN, TLUMIP, TRANUS, DELTA and URBANSIM has detailed urban land and housing market sub-models.

The Transportation sub-model Two main types of transportation sub-models exist in operational Land Use and Transportation Interaction (LUTI) modeling frameworks: Four-step and Activity-based models. The traditional Four-step approach involves a sequence of four stages - trip generation, trip distribution, mode choice, and route assignment - to model travel demand (McNally [2000]). In trip generation, the number of trips generated by households and businesses is estimated based on socioeconomic and land use factors. In trip distribution, the spatial pattern of trips is estimated, often using gravity models. In mode choice, the mode of transportation for each trip is estimated based on factors such as travel time, cost, and availability. Finally, in traffic assignment, the trips are assigned to specific routes, and volumes are estimated (de Dios Ortúzar and Willumsen [2011]).

On the other hand, Activity-based models offer a more behaviorally-oriented approach (such as aggregate utility-based, microsimulation, and other methods in LUTI modeling) to capture travel behavior by modeling the underlying activities that generate trips (Acheampong and Silva [2015]). Activity-based transportation sub-models have been developing since the 1990s, offering potential advantages such as the ability to model behavioral responses to travel demand management policies and avoiding weak assumptions inherent in aggregate spatial interaction models (Wegener [2004]). However, despite these benefits, activity-based transportation sub-models remain slow in adoption and use in practice (Rasouli and Timmermans [2014], Recker [2001]). Instead, most existing operational LUTI models still rely on the traditional Four-step approach as their transportation sub-model. This is likely due to the complexity of Activity-based models, which require more data and computational resources to implement compared to the Four-step approach. Additionally, the Four-step approach is more familiar and easier to interpret for policymakers and practitioners (Rasouli and Timmermans [2014]).

As the Figure 2 illustrates, the land-use and transportation sub-models are connected in a way that the transportation sub-model includes a component that assigns trips to specific routes in the transportation network based on the land-use data. In contrast to the fixed nature of transportation networks in most transportation sub-models, the coupling between the land-use and transportation sub-models is dynamic, meaning that changes in land-use and transportation can influence each other (Acheampong and Silva [2015]). The transportation sub-models used in many models hold the extent and capacity of transportation networks constant or treat them as policy variables, which limits the ability to capture evolutionary dynamics in transportation networks (Iacono et al. [2008]). However, the transportation sub-models account for factors such as congested networks, travel times, and distance, affecting generalized transport costs. Using the transport costs calculated by the transportation sub-models, accessibility indexes can measure how easy or difficult it is to access different locations from different starting points (Geurs et al. [2012], Hanson [2004]). These accessibility indexes are then fed back into the land-use system, where they can influence the land-use patterns. This feedback loop allows the two sub-models to interact and evolve over time. In the following, UrbanSim model will be explained as one of the most frequently used LUTI models, including its structure and processing.

2.5 UrbanSim

UrbanSim (Waddell [2000, 2002], Waddell and Ulfarsson [2004], Waddell et al. [2006], Guide [2011]) is an extensible agent-based urban simulation model developed by Paul Waddell and his team first at the University of Washington, Seattle, later at the University of California, Berkeley. The model was initially developed in 1996 as part of the Transportation and Land Use Model Integration Project (TLUMIP) initiated by the Oregon Department of Transportation (Waddell [2002]). The original UrbanSim model was designed to work in conjunction with a traditional four-step model in Eugene-Springfield and got developed to run with an activity-based travel model in Honolulu, Hawaii (Hunt et al. [2005]).

2.5.1 Data requirements and preparation

UrbanSim models take the base year data, access indicators from the external travel model, and control totals derived from external macroeconomic forecast models as the input. In UrbanSim, the base year data store contains the initial state of a scenario (Waddell [2000]). It represents chosen attributes of persons, jobs, real estate, and locations, and the mapping among these attributes (Waddell [2002]). The database typically contains geographies, initial household, and job information for a given base year. The geographic layer represents administrative boundaries. Households are represented as objects with the necessary attributes to model location choices. Persons are associated with households and exhibit characteristics related to travel behavior. Finally, the database includes job entries incorporating the employment sector, representing employment (Waddell [2002]). The primary sources of the base year data are usually surveys or censuses. The population synthesizer in OPUS (Open Platform for Urban Simulation) can be utilized if disaggregated data is unavailable.

2.5.2 Model structure and processing

UrbanSim has a modular structure with sub-models that can be estimated and run independently and uses a dynamic disequilibrium approach, with all sub-models interacting in a period-based temporal framework. UrbanSim does not model transport itself; it relies on interaction with external transport models (Wegener [2004]) to update traffic conditions. UrbanSim might be better described as an urban simulation system, consisting of six components reflecting the decisions of households, businesses, developers, and governments (as policy inputs) as well as their interactions in the real estate market (Waddell [2000], Bierlaire et al. [2015]). The responsible components are the Econometric and Demographic Transition Models, the Household and Employment Mobility Models, the Household and Employment Location Models, the Real Estate Development Model, and the Real Estate Price Model.
During the simulation, the processing sequence of six models is usually as follows (Bierlaire et al. [2015]):

Accessibility Model links land use and transport, taking the output data provided by the external travel model and maintaining accessibility patterns for the internal UrbanSim models. The household and employment location models and the real estate price model use this output.

Econometric and Demographic Transition Models simulate population births and deaths and the creation and loss of jobs. Newly created households and jobs still need to have a location.

Household and Employment Mobility Models (relocation model) replicate the relocation of households or jobs. When a household or job decides to relocate, they are placed in a queue and assigned a new location by their location choice models. Their current location becomes vacant.

As a result, they change the real estate vacancy conditions used in the real estate development and price model.

Household and Employment Location Models determine the location assignment through a three-step process. For households, a random sample of vacant residential units is chosen first. In the second step, the desirability of the selected units is assessed using a multinomial logic (MNL) model based on the variables and estimated coefficients included in the household location choice model (HLCM). Finally, households select their most desired location. The employment location choice model (ELCM) approach is quite similar, except that the new job location is selected randomly among a random sample of possible locations.

Real Estate Development Model (developer model) simulates developer decisions such as new construction, innovation, and reconstruction of existing structures and the type of development. It considers all geographical units analysis (GUA), such as grid cells, for which development is allowed. A multinomial logit model evaluates each GUA for possible development types, including the option of no development.

Real Estate Price Model (REPM) predicts property or GUA prices based on location characteristics such as neighborhood accessibility and policy effects. The resulting land values are used as input in the Household and Employment Location Models, as well as the Real Estate Development Model, in the next UrbanSim iteration. The structure and processing sequence of UrbanSim is shown in Figure 3 .

3 SCGE (Spatial Computable General Equilibrium) models

One of the fundamental principles of spatial economics is the crucial role of transport infrastructure and quality of service for regional development. There is a broad spectrum of theoretical approaches originating from different scientific disciplines and intellectual traditions to explain this role. Ellsworth [1933] at the pinnacle of neoclassical theory, proposed that under perfect competition, factor mobility, and constant returns to scale, interregional flows of capital, labor, and trade will result in equal prices of production factors and goods in all regions (Wegener [2011]). The opposite viewpoint taken by Perroux [1955] and Myrdal and Sitohang [1957] argued that the economies of scale and spatial impedance on mobility cause the presence of advanced industries would result in spatial polarization between prospering and lagging regions (Wegener [2011]).

A synthesis between the two opposing views was offered by the New Economic Geography (NEG) (Krugman [1992], Krugman and Venables [1995], Fujita et al. [2001]). A theory of the emergence of large agglomerations relying on increasing returns to scale and transportation costs that "invaded"the field of spatial economics in the early 1990s. Krugman [1991] was one of the first to recognize that the spatial pattern of production and consumption needed to be studied within a general equilibrium framework, and that the assumption of perfect competition and constant returns to scale needed to be abandoned in order to explain the agglomeration of economic activity. Following Krugman, multiregional input-output models with a characteristic of NEG models are today called Spatial Computable General Equilibrium (SCGE) models, although the term CGE originally had a broader meaning (Bröcker and Mercenier [2011], Wegener [2011]).

SCGE models are spatial extensions of numerically solvable general equilibrium models and capture the interactions between different sectors and regions of the economy. In a general

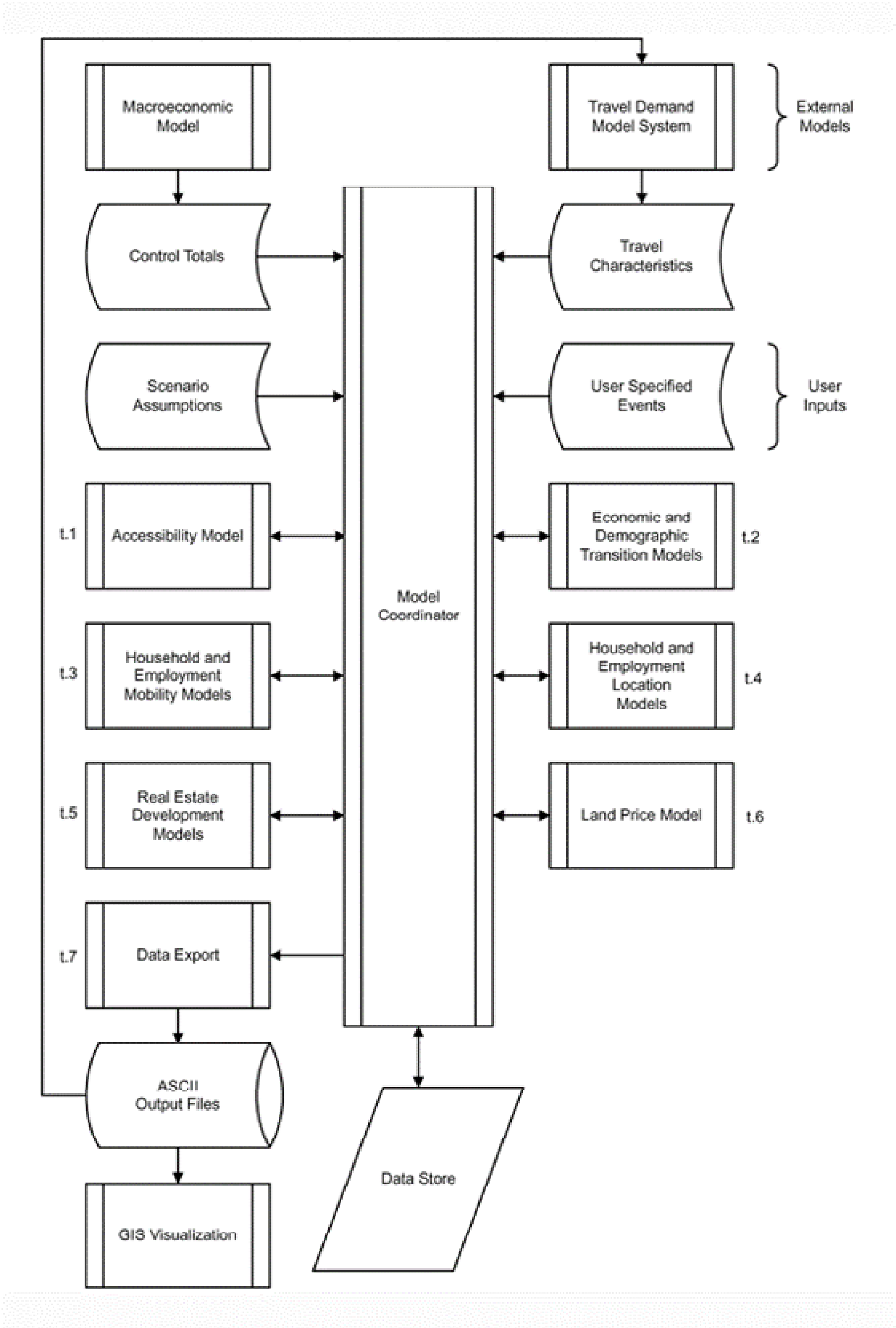

Figure 3: The structure and processing sequence of UrbanSim (adapted from Waddell 2002)

equilibrium model, the trade-off problems between various economic agents are solved through the price mechanism (Tavasszy et al. [2011], Hansen and Johansen [2017], Hansen and Ivanova [2012]). SCGE models are comparative static equilibrium models of interregional trade and location, primarily based on microeconomics but generally applied at a more aggregate, sectoral level. These models use utility and production functions with input substitution, typically modeled using constant elasticity of substitution (CES) equations (Tavasszy et al. [2011]). Firms in these models often operate under economies of scale within markets characterized by monopolistic competition, following the Dixit-Stiglitz (Dixit and Stiglitz [1977]) type.

The current SCGE models have a sophisticated theoretical foundation and employ non-linear mathematics (Tavasszy et al. [2011], Hansen and Johansen [2017], Hansen and Ivanova [2012]). This allows them to incorporate features such as (dis)economies of scale, external economies related to spatial clusters of activity, continuous substitution between capital, labor, energy, and material inputs for firms, and substitution between different household consumption goods.

3.1 A review of SCGE model

(Debreu [1959]) and (Arrow et al. [1971]) are two classic references in theoretical general equilibrium analysis. The model developed by Bröcker [1998] was the first CGEurope example of an SCGE model and provided the basis for many subsequent CGEurope models such as (Broecker et al. [2004], Sundberg [2005], Ivanova et al. [2007], Heyndrickx et al. [2009], Brandsma et al. [2011], Heyndrickx et al. [2011]). Some other examples of SCGE models are RAEM (the latest version being RAEM 3.0) and REMI (with the latest version being PI+ or Policy Insight).

The CGEurope model, developed at the University of Kiel, is a multiregional spatial computable general equilibrium model that takes into account transport costs as expenditures of firms for transport and business travel (Bröcker [1998], Broecker et al. [2004], Bröcker and Mercenier [2011]). This model has been utilized in numerous EU projects, including IASON, ESPON 2.1.1, and TEN-CONNECT (Wegener, M. 2011).

The RAEM model, developed at the University of Groningen and TNO Delft, is a spatial computable general equilibrium model that incorporates regional capital investment and stock and flow relationships of households and firms (Oosterhaven et al. [1998], Ivanova et al. [2007], Wegener [2011]). The latest version, RAEM 3.0, includes international trade and interregional migration and determines the equilibrium of supply and demand and interregional trade flows in each time period. RAEM was initially designed for the Netherlands and has been used in a simplified version (RAEM-Light) in Hungary, Japan, and South Korea.

Hansen and Johansen [2017] formulated a RAEM model to quantify the direct user benefits and the Wider Economic Impact (WEI) of nine planned Norwegian transport infrastructure projects for the 2018-2029 Norwegian National Transport Plan. The model is an extension of PINGO and part of the RAEM family of SCGE models (Ivanova et al. [2007]). (Heyndrickx et al. [2011] described the construction and first empirical application of the TIGER (Transport and Infrastructure General Equilibrium model for Regions) model. The model belongs to SCGE models based on the methodology of the RAEM and ISEEM models and is constructed as a flexible tool for policy analysis and a tool for cost-benefit analysis of infrastructure projects on the level of the Benelux.

Oosterhaven et al. [2001] developed an SCGE (RAEM) model to estimate the indirect economic effects of major transport infrastructure projects on Dutch regions. The first version of the model was applied to a base scenario for the year 2020 and used to assess the indirect economic effects of a new railway link between Amsterdam and Groningen. The model employs monopolistic competition for fourteen sectors as the basic market form and calibrates most of its coefficients on recently constructed bi-regional input-output tables for the Netherlands.

The REMI model, initially a multiregional input-output model with final endogenous demand, was developed at the University of Massachusetts (Treyz [1980], Treyz et al. [1991]) and has since undergone several revisions. Its latest version, PI+ or Policy Insight, is a new economic geography extension of the original REMI framework (Flyvbjerg [2008]). Previous generations of the REMI model have been widely applied for policy analyses in over a hundred regional and state agencies in North America and Europe (Wegener [2011]).

3.2 The structure of a SCGE model

The SCGE model comprises households, firms, and governments in different regions. Each region produces a set of goods and services that are traded with other regions. The model assumes that firms choose their locations based on relative production costs in different regions, leading to spatial agglomeration. The model includes transport costs and trade barriers that affect the flow of goods and services between regions. The model's formulation involves solving a set of nonlinear equations representing equilibrium conditions for each household, firm, and government in each region based on assumptions of utility and profit maximization and government budget constraints, as well as market-clearing conditions that ensure that the supply and demand for goods and services, labor, and capital are balanced in each region. The following presents a brief overview of a version of the SCGE model developed by Krugman [1991]. The model is a simple illustrative model, offering valuable insights into a fundamental question in economic geography: why and when does manufacturing concentrate in a few regions, leaving others relatively undeveloped? By utilizing models and techniques derived from theoretical industrial organization, this model sheds light on the factors and circumstances that contribute to this spatial concentration phenomenon, thereby providing new perspectives on the interplay between economic and geographic factors.

Krugman' s model

Krugman [1991]' s model is a "centre–periphery"model seeks to explain how countries/regions can internally develop into industrialized "cores"and agricultural "peripheries". This model represents a two-region geography where two kinds of production are assumed: agriculture, which is a constant-returns sector tied to the land, and manufactures, an increasing-returns sector that can be located in either region. It is a variant of the monopolistic competition framework initially proposed by Dixit and Stiglitz [1977] where all individuals in the economy are assumed to share a basic utility function:

$$U = C_M^{\mu} C_A^{1-\mu} \tag{1}$$

C_A refers to the consumption of agricultural goods and C_M represents the total consumption of manufactured goods. The parameter μ represents the share of expenditure allocated to the consumption of manufactures. It determines the weight or importance individuals place on consuming manufactured goods relative to agricultural goods. This share is one of the key parameters for determining whether a region converges or diverges. C_M can be defined by:

$$C_M = \left[\sum_{i=1}^{N} c_i^{(\sigma-1)/\sigma} \right]^{\sigma/(\sigma-1)} \tag{2}$$

Where N is a large number of potential products and $\sigma > 1$ is the substitution elasticity among the products. The elasticity σ is the second parameter determining the character of equilibrium in the model, which is assumed to be equal to $\sigma = \frac{1}{1-p}$.

It is assumed that each region has two factors of production. To simplify the analysis based on Krugman [1981]'s suggestion, each factor is assumed to be specific to one sector. Specifically, peasants are responsible for producing agricultural goods, and for the sake of simplicity, it is assumed that one unit of labor is required for agricultural production. The peasant population is considered completely immobile between regions, with a given peasant supply of $\frac{(1-\mu)}{2}$ in each region. On the other hand, workers may move between regions. The worker supply in region 1 and 2 is L_1 and L_2 respectively, with the requirement that the total worker supply across both regions equals the overall number of workers in the economy represented as:

$$\mu = L_1 + L_2 \tag{3}$$

The production of each manufactured good i consists of fixed costs and constant marginal costs, giving rise to economies of scale;

$$L_{Mi} = \alpha + \beta x_i \tag{4}$$

Where L_{Mi} is the amount of labor used in the production of good i and x_i is the total production amount of the good.

Transportation costs

Two strong assumptions are made to ensure tractability concerning the structure of transportation costs. First, transportation costs in the agricultural regions are free of charge. This means that the price of agricultural goods, and thus wages, are the same in both regions. Second, transportation costs for manufactured goods are assumed to take Samuelson's "iceberg" form in which transportation costs are calculated based on the fraction of the good that does not reach the destination Samuelson [1954]. Specifically, of each unit of manufactures shipped from one region to the other, only a fraction $\tau < 1$ arrives. This fraction τ, which serves as an inverse index of transportation costs, is the final parameter determining whether regions converge or diverge.

Profit maximization

A large number of manufacturing firms are supposed, each produces its own product (monopoly). The profit-maximizing pricing behavior of a representative firm in region i is therefore to set a price equal to:

$$p_i = \frac{\sigma}{\sigma - 1} \beta w_i \tag{5}$$

Where w_i is the wage rate of the workers in region i. By comparing prices for representative products in regions 1 and 2, we get:

$$\frac{p_1}{p_2} = \frac{w_1}{w_2} \tag{6}$$

If there is free entry of firms into manufacturing, profit must be driven to zero;

$$(p_i - \beta w_i) = \alpha w_i \tag{7}$$

which further implies;

$$x_1 = x_2 = \alpha(\sigma - 1) \tag{8}$$

That is the amount of output is the same in each region, regardless of wage rates, relative demand, etc. This implies that the number of goods produced in each region is proportional to the number of workers;

$$\frac{n_1}{n_2} = \frac{L_1}{L_2} \tag{9}$$

Market equilibrium

This model lacks any explicit dynamics, but still analyzing short-run equilibrium can provide insights before examining the concept of full equilibrium. The analysis of short-run equilibrium begins by looking at the demand within region 1 for products of the two regions. Let c_{11} and c_{12} be the demand in region 1 for products from regions 1 and 2, respectively. The price of a local product is simply its f.o.b. price p_1, while the price of a product from the other region, however, is its transport-cost-inclusive price $\frac{p_2}{\tau}$. Then the relative demand for the products of the two regions is:

$$\frac{c_{11}}{c_{12}} = \left(\frac{p_1 \tau}{p_2}\right)^{-\sigma} = \left(\frac{w_1 \tau}{w_2}\right)^{-\sigma} \tag{10}$$

z_{11} represents the ratio of spending on local manufactures compared to spending on manufactures from another region. Two points regarding z_{11} are: First, a one percent increase in the relative price of goods from region 1 leads to a σ percent decrease in the quantity sold, but the overall value decreases by only $(\sigma - 1)$ percent, because of the valuation effect. Second, as region 1 produces more goods, its share of overall expenditure will increase, regardless of the relative prices of goods. Then we have:

$$z_{11} = \frac{n_1}{n_2} \cdot \left(\frac{p_1 \tau}{p_2}\right) \cdot \frac{c_{11}}{c_{12}} = \frac{L_1}{L_2} \cdot \left(\frac{w_1 \tau}{w_2}\right)^{-(\sigma-1)} \tag{11}$$

Corresponding ratio for region 2:

$$z_{12} = \frac{L_1}{L_2} \left(\frac{w_1}{w_2 \tau}\right)^{-(\sigma-1)} \tag{12}$$

The total income earned by workers in region 1 is equivalent to the total amount spent on products in both regions. (Transportation costs are included because they are assumed to be incurred in the goods themselves). Let Y_1 and Y_2 represent the regional incomes, which include the wages of peasants. Then the total income of region 1 workers is:

$$w_1 L_1 = \mu \left[\frac{z_{11}}{1 + z_{11}} Y_1 + \frac{z_{12}}{1 + z_{12}} Y_2\right] \tag{13}$$

and the total income of region 2 workers is:

$$w_2 L_2 = \mu \left[\frac{1}{1 + z_{11}} Y_1 + \frac{1}{1 + z_{12}} Y_2\right] \tag{14}$$

However, the incomes of the two regions depend on the distribution of workers and their wages. Recalling that the wage rate of peasants is the numeraire, we have:

$$Y_1 = \frac{1 - \mu}{2} + w_1 L_1 \tag{15}$$

and

$$Y_2 = \frac{1 - \mu}{2} + w_2 L_2 \tag{16}$$

The set of equations 1-16 may be regarded as a system that determines w_1 and w_2, as well as four other variables, given the distribution of labor between regions 1 and 2. If the amount of labor is equal in both regions ($L_1 = L_2$), then the wages will also be equal ($w_1 = w_2$). However, if labor moves to region 1, the relative wage rate ($\frac{w_1}{w_2}$) can change due to two opposing effects: the competition effect and the demand effect (see Figure 4).

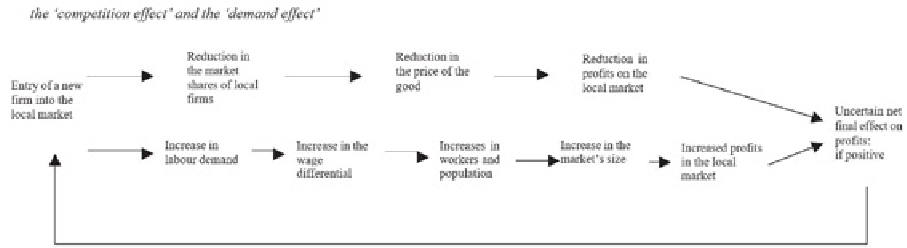

Figure 4: The virtuous cumulative development circle of the 'new economic geography' adopted from Capello [2015]

long-run equilibrium

When transitioning from short-run to long-run equilibrium, an additional factor comes into play. Workers are concerned with real wages rather than nominal wages. To quantify this, $f = \frac{L_1}{\mu}$ is defined as the share of the manufacturing labor force in region 1. Consequently, the true price index for manufactured goods consumed by residents of region 1 is denoted as:

$$P_1 = \left[f w_1^{\sigma-1} + (1-f) \left(\frac{w_2}{\tau} \right)^{-(\sigma-1)} \right]^{-\frac{1}{\sigma-1}} \tag{17}$$

And for consumers residing in region 2 is:

$$P_2 = \left[\left(f \left(\frac{w_1}{\tau} \right) \right)^{-\sigma+1} + (1-f) w_2^{-(\sigma-1)} \right]^{-\frac{1}{\sigma-1}} \tag{18}$$

The real wage of the workers in each region is then:

$$\omega_1 = w_1 P_1^{-\mu} \tag{19}$$

and

$$\omega_2 = w_2 P_2^{-\mu} \tag{20}$$

Considering equations 17 and 18, it is evident that when wage rates are initially equal, a shift of workers from region 2 to region 1 lowers the price index in region 1 and raises it in region 2. Consequently, the real wages in region 1 will be higher compared to region 2, adding another factor for regional divergence.

The crucial question is how the ratio of wages ($\frac{\omega_1}{\omega_2}$) varies with the distribution of workers (f). When f equals $\frac{1}{2}$ (equal numbers of workers in both regions), the two regions offer equal real wage rates due to symmetry. However, the stability of this equilibrium depends on whether $\frac{\omega_1}{\omega_2}$ decreases or increases with f. If $\frac{\omega_1}{\omega_2}$ decreases with f, whenever one region has a larger workforce than the other, workers will tend to migrate out of that region. This leads to regional convergence as the workforce balances between the regions. Conversely, if $\frac{\omega_1}{\omega_2}$ increases with f, workers will tend to migrate to the region that already has more workers, resulting in regional divergence. So, there are two forces working towards divergence (the home market effect and the price index effect) and one force working towards convergence (degree of competition for the local peasant's market). The question raised is which forces dominate the outcome in terms of convergence or divergence.

In order to determine which forces dominate, it is noted that there are only three parameters in this model that cannot be eliminated by choice of units: the share of expenditure on manufactured goods, μ; the elasticity of substitution among products, σ; and the fraction of a good shipped that arrives, τ. Figure 5 makes the point. It illustrates the relationship between the computed values of $\frac{\omega_1}{\omega_2}$ and f in two different scenarios. Both scenarios assume $\sigma = 4$ and $\mu = 0.3$. In one case, $\tau = 0.5$, representing high transportation costs, while in the other case, $\tau = 0.75$, representing low transportation costs. In the high transport cost scenario, the relative real wage decreases as f increases, indicating regional convergence. This suggests that the geographical distribution of the "second stratum" would follow that of the first. In contrast, in the low transport cost scenario, the slope is reversed, indicating regional divergence.

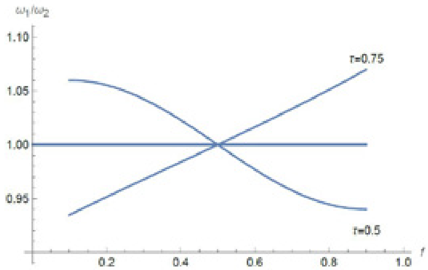

Figure 5: Computed values of $\frac{\omega_1}{\omega_2}$ as a function of f in two different cases

Convergence vs. divergence

When examining regional divergence, a valuable approach is to reverse our usual method. Instead of focusing on whether an equilibrium with equal distribution of workers across regions is stable, we can consider the stability of an equilibrium where all workers are concentrated in a single region.

So, a scenario is considered where all workers concentrate in Region 1, making it a larger market compared to Region 2. Since a share of total income μ is spent on manufactures, and all of this income goes to Region 1, we have:

$$\frac{Y_2}{Y_1} = \frac{1-\mu}{1+\mu} \tag{21}$$

Let n be the total number of manufacturing firms. Each firm's sales value, V_1, is precisely set to allow them to make zero profits.

$$V_1 = \frac{\mu}{n}(Y_1 + Y_2) \tag{22}$$

Now the question arises: Is it possible for an individual firm to commence production profitably in region 2? This hypothetical firm, referred to as a "defecting firm," determines whether concentration of production in region 1 is an equilibrium. If it is not possible for a firm to be profitable in region 2, then the equilibrium lies in the concentration of production in region 1.

To attract workers to the firm in region 2, the firm must offer higher wages compared to region 1. This higher wage compensates the workers for the fact that they would need to rely on imported goods for their consumption needs because of the limited manufacturing industry in region 2.

$$\frac{w_2}{w_1} = \left(\frac{1}{\tau}\right)^{\mu} \tag{23}$$

Given higher wages, the firm will have a profit-maximizing price that is higher than that of the other firms in the same proportion. So, the total value of the defecting firm's sales will be:

$$V_2 = \frac{1}{n}\left[\left(\frac{w_2}{w_1\tau}\right)^{-(\sigma-1)} Y_1 + \left(\frac{w_2\tau}{w_1}\right)^{-(\sigma-1)} Y_2\right] \tag{24}$$

Using equations 22, 23, and 24 and manipulating them, it is possible to obtain the ratio between the sales value of the defecting firm and of the firms in region 1;

$$\frac{V_2}{V_1} = \frac{1}{2}\tau^{\mu(\sigma-1)}\left[(1+\mu)\,\tau^{(\sigma-1)} + (1-\mu)\tau^{-(\sigma-1)}\right] \tag{25}$$

Due to the higher wage rate in region 2, fixed costs are also higher. So, for it to be profitable for the firm to move to region 2, the following must be met: $\frac{V_2}{V_1} > \frac{w_2}{w_1} = \tau^{-\mu}$. Therefore, a new variable ν must be defined;

$$\nu = \frac{1}{2}\tau^{\mu\sigma}\left[(1+\mu)\,\tau^{(\sigma-1)} + (1-\mu)\tau^{-(\sigma-1)}\right] \tag{26}$$

When $\nu < 1$, it is not profitable to establish in region 2 if all other manufacturing production is concentrated in region 1. Thus, in this case, regional divergence is the long-term equilibrium.

Equation 26 defines a boundary that separates convergence and divergence based on critical parameter values. To analyze this equation, one only needs to evaluate it near $\nu = 1$ and determine how each of the three parameters must change to counterbalance a change in any of the other parameters.

By taking the derivative of ν with respect to μ, we find that:

$$\frac{\partial v}{\partial \mu} = v\sigma \ln\tau + \frac{1}{2}\tau^{\sigma}\mu\left(\tau^{\sigma-1} - \tau^{-(\sigma-1)}\right) < 0 \tag{27}$$

The larger the share of income spent on manufactured goods, the lower the relative sales of the defecting firm. This occurs due to two reasons. Firstly, workers require higher wages to move to the second region. Secondly, as the share of expenditure on manufactured goods increases, the size of the market in region 1 grows, resulting in a stronger home market effect.

By taking the derivative of v with respect to τ, we have:

$$\frac{\partial v}{\partial \tau} = \frac{\mu\sigma v}{\tau} + \frac{\tau^{\mu\sigma}(\sigma-1)}{2\tau}\left[(1+\mu)\tau^{\sigma-1} - (1-\mu)\tau^{-(\sigma-1)}\right] \tag{28}$$

Figure 6 indicates v as a function of τ; at low levels of τ (i.e., high transportation costs), v exceeds 1, indicating that it is profitable to defect or establish manufacturing in a different region. However, at a critical value of τ, v falls below 1, indicating that concentrated manufacturing in region 1 is an equilibrium, and the relative value of sales approaches 1 from below. The key insight from this graph is that at the critical value of τ, which marks the boundary between convergence and divergence, $\frac{\delta v}{\delta \tau}$ is negative. That is, higher transportation costs work against regional divergence.

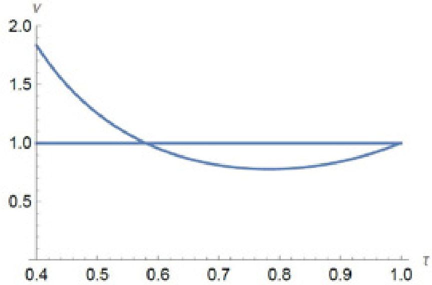

Figure 6: ν as a function of τ

By taking the derivative of v with respect to σ, we have:

$$
\begin{aligned}
\frac{\partial v}{\partial \sigma} &= \ln \tau \left(\mu v + \frac{1}{2} \tau^{\mu\sigma} \left[(1+\mu)\tau^{\sigma-1} - (1-\mu)\tau^{-(\sigma-1)} \right] \right) \\
&= \ln \tau \left(\frac{\tau}{\sigma} \right) \left(\frac{\partial v}{\partial \tau} \right)
\end{aligned} \tag{29}
$$

Since we have seen that $\frac{\delta v}{\delta \tau}$ is negative at the specific point, this implies that $\frac{\delta v}{\delta \sigma}$ is positive. In other words, a higher elasticity of substitution (which also indicates lower economies of scale at equilibrium) acts as a deterrent to regional divergence.

Results

These results can be visualized through a diagram. When σ is held constant, a "phase boundary" can be depicted in the space of μ and τ. This boundary represents the parameter values at which firms are indifferent between remaining concentrated in region 1 or defecting. If an economy lies within this boundary, it will not experience significant industry concentrations in either region. On the other hand, if an economy lies outside the boundary, it will exhibit such concentrations. The slope of this boundary is:

σ is held constant;

$$\frac{\partial v}{\partial \mu} = -\frac{\left(\frac{\partial v}{\partial \mu}\right)}{\left(\frac{\partial v}{\partial \tau}\right)}$$

μ is held constant;

$$\frac{\partial v}{\partial \sigma} = -\frac{\left(\frac{\partial v}{\partial \sigma}\right)}{\left(\frac{\partial v}{\partial \tau}\right)}$$

The figure 7 illustrates that an increase in σ results in an outward shift in the μ, τ space. The figure provides an interesting observation about the relationship between τ, μ, σ and the distribution of manufacturing production in an economy. In an economy characterized by high transportation costs, a small proportion of footloose manufacturing, and/or weak economies of scale, the distribution of manufacturing production is primarily influenced by the distribution of the "primary stratum" of peasants. However, as transportation costs decrease, the manufacturing sector's share expands, and economies of scale become more robust, circular causation comes into play. Consequently, manufacturing becomes concentrated in the region that initially gains an advantage.

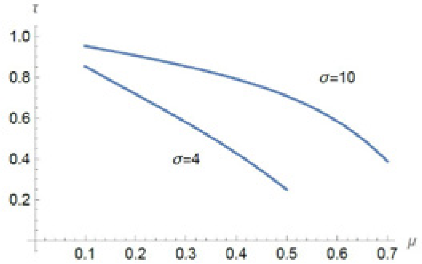

Figure 7: Calculated boundaries in μ,τ space for two values of σ

3.3 Applications of SCGE models and Challenges in applying SCGE models for transportation analysis

SCGE (Spatial Computable General Equilibrium) models are frequently used as impact estimation tools in economic analysis. They provide a theoretically robust method for computing the wider economic impacts (WEI) in cost-benefit analysis (Koopmans and Oosterhaven [2011]). These WEI represent the welfare effects that arise due to market imperfections in sectors linked to transportation and are not factored into conventional cost-benefit analyses that only consider the benefits accruing to transportation users (Hansen and Johansen [2017]). The indirect effects of transportation, which are additional to the first-order direct cost reductions, can be termed "multiplier effects "or "second-order effects ". According to literature, the magnitude of these effects can approach almost 80% of the direct impacts (Broecker et al. [2004], Tavasszy et al. [2011]).

Several challenges associated with employing spatial computable general equilibrium (SCGE) models for transportation assessment have been mentioned in (Tavasszy et al. [2011, 2002]): The transport system contributes to the spatial economy through the costs of transport services. Typically, in transport evaluation practice transport models are applied to feed SCGE models with cost changes in the transport sector as a result of policy measures. SCGE models focus on spatial interactions between regions based on production and consumption. However, they must consider the choices concerning alternative services offered within the transport system. Entering transport to SCGE models can lead to practical challenges that have not been resolved and cannot be addressed soon due to limitations in available data. Some of these challenges are already familiar to Land Use-Transport Interaction (LUTI) models, which do not incorporate a rigorous economic framework comparable to SCGE models. Furthermore, SCGE models must account for the impact of transport costs on the production of goods and services, which can be challenging to model accurately. The conventional, micro-level specification of product variety in aggregate applications is another challenge. SCGE models typically use an aggregate representation of product variety, which can obscure important details about the underlying economy.

4 Spatial equilibrium models representing an alternative in between standard SCGE and Large-scale models

McArthur et al. [2014] formulated a new spatial equilibrium model to explore, for instance, how changes in the transportation network and the distribution of jobs may cause rural depopulation. The authors discuss that a large-scale model is not suitable for analyzing typical Norwegian regions due to their non-metropolitan nature. Large-scale models focus excessively on small details, which may not be necessary for analyzing these regions effectively. Also, the SCGE model, being too macroscopic, provides a broad overview and does not capture smaller details, making both models inadequate for analyzing typical Norwegian regions. Thus, the objective of McArthur et al. [2014] was to develop a model that struck a balance between the two approaches. To achieve this, they constructed a spatial equilibrium model that deviated from standard SCGE models by considering intraregional commuting and shopping patterns, features that are typically associated with large-scale models.

Spatial equilibrium and migration dynamics
The central idea of the model is the concept of spatial equilibrium, which refers to a state in which intraregional migration and commuting flows are in balance with a specific spatial distribution of jobs and workers across different zones. Like most spatial equilibrium models, the model incorporates the core elements of economic base modeling (Goldner [1971], Lowry [1964]). Therefore two types of firms are defined in the model. Local-sector firms' activity is determined by intraregional demand, whereas production in basic-sector firms is determined by factors unrelated to intraregional demand. The model considers three types of spatial mobility: migration, commuting, and nonwork-related trips between zones.

The migration between different zones is modeled through an absorption effect analogous to the basic idea in the theory of intervening opportunities (Stouffer [1940]). The idea is that the worker moves to the first zone where the conditions are acceptable. Another central hypothesis is that distance (converted to a generalized cost in the model) limits spatial interaction. A symmetric matrix that considers the cost deterrence and absorption effects is normalized to create a migration probability matrix. The system's equilibrium solution is then determined using this matrix.

Spatial distribution of jobs in the model: basic-sector and local-sector
The model assumes the spatial distribution of basic-sector jobs to be exogenous, and to model the spatial distribution of local-sector activity, it utilizes the approach based on Gjestland et al. [2006]. The idea is that the trip frequency to different locations will depend upon the local availability of the activity in question and on the travel costs to each location at which the activity is available (Handy [1992], Krizek [2003]). Considering economies of scale, transportation costs, and agglomeration benefits, the local-sector density will be high in the regional center and low in the suburbs, and it will approach the regional average as the distance (generalized cost) from the center increases. This means that the intraregional distribution of local-sector jobs reflects the residential location pattern. At the same, it makes sense to assume that job opportunities within a reasonable commuting distance affect residential location decisions, so the model considers that the spatial distribution of jobs and people is interdependent.

The relationship between the spatial distribution of jobs and people, an economic base multiplier process
The economic base (EB) multiplier is a widely used tool in regional analysis. Its operation is typically explained from a Keynesian perspective, as discussed by Daly [1940], Richardson

[1985] and Tiebout [1962]. In line with this perspective, an increase in external demand leads to expanded activity in the basic (export) sector, subsequently generating increased activity in the nonbasic (non-traded) sector through heightened intermediate and consumption demand. The model assumes that all industries have excess capacity and that the labor supply is infinitely elastic due to either involuntary unemployment or interregional migration. In this framework, supply is considered passive, resulting in the increase in demand solely affecting output (McGregor et al. [2000]).
So, the economic base mechanism represents a more direct interdependency between the spatial distribution of jobs and the spatial distribution of people. Consider a zone where basic-sector activity has increased. This increases labor demand and attracts labor to the zone. So, the demand for goods and services produced in the local sector increases too. This creates labor demand this time for local-sector goods and initiates a positive growth cycle, known as an economic base multiplier process.

Migration in the model
The residential location choice can be seen as a two-step process. Firstly, households must decide whether to move from their current residence. Secondly, if they choose to move, they must select from various alternative locations. The model accounts for the possibility that staying in a zone is affected by both the labor-market accessibility of the zone and the local labor-market situation of the zone. The hypothesis that the probability of remaining in a zone is positively related to the labor-market accessibility of the zone is consistent with the findings from Swedish microdata (Eliasson et al. [2003], Lundholm [2010]) and similar work in the Netherlands (Van Ham and Hooimeijer [2009]). To represent the labor-market accessibility in the model, they measure the generalized cost to reach all other regional zones. Each zone is weighted by the number of jobs available, adjusted for job competition as measured by the ratio of available jobs to local job seekers. The weights also involve a cost deterrence function that places a relatively high weight on destinations that can be reached at a low cost from the residential location. The measure of generalized cost is finally combined with information on the local labor-market situation in the function that determines the probability that workers move from a specific zone. To explain it, assume that a zone has high unemployment. If this zone is centrally located in the region, workers most likely choose to commute rather than move. However, if accessibility is low, migration will be a more common reaction to high unemployment.

Interdependent migration probabilities
The model explicitly considers the possibility that migration probabilities may be interdependent. The hypothesis is that if a zone's population drops below a certain threshold, the likelihood of migration from that zone may increase. Because then institutions providing essential community services might have to close. The threshold may differ between services/businesses, such as a school, post office, bank, or grocery store (Berry and Garrison [1958], Henderson and Taylor [2003], Parr [1966]). This is a main idea of central place theory [see Berry and Garrison [1958] for a discussion].

An example of applying this spatial equilibrium model is examining the potential effects of changes in the transportation network and job distribution on rural depopulation. The model captures complex nonlinearities and can generate counterintuitive results, which are crucial for policymakers to understand. McArthur et al. [2014] found that in certain cases, where a peripheral zone has a low number of basic-sector jobs, a situation can arise where interdependent migration decisions and an economic base multiplier mechanism come into play. This leads to an equilibrium solution where the zone experiences a significant decrease in population and employment. Using numerical experiments allows researchers to study how the existence and location of such a bifurcation point depend on migration, travel, and labor-market behavior. McArthur et al. [2014] suggest that the likelihood of a rural zone being completely depopulated increases as the willingness to migrate over long distances decreases. They also concluded that a negative shock that increases the generalized cost of traveling between two zones could initiate a process of rural depopulation. It is important to note that negative and positive shocks do not necessarily have symmetric effects on the equilibrium population of a rural zone. This reflects a case of hysteresis, which is a characteristic of nonlinear mathematical models with multiple equilibria.

5 An agent-based microsimulation model for our study

We developed an agent-based microsimulation model to generate spatial interaction data from a demographically similar population in Norway. The model aims to study how commuting flows, and specifically how estimates of the distance deterrence parameter, respond to spatial structure characteristics such as changes in the road transportation infrastructure, the compactness of the system of towns in the geography, the clustering of local and basic sector jobs, and where the central business district is located. We also demonstrate how the trip distribution depends on labor or housing market conditions and how this is reflected in the estimates of the distance deterrence parameter. Additionally, we address how household preferences and different aspects of the budget constraint affect travel demand.

According to (Wegener [2004]), the most promising technique for activity-based land use and transport modeling is microsimulation which makes it possible to reproduce the complex spatial behavior of individuals on a one-to-one basis. The main advantage of microsimulation, compared to other activity-based modeling, is its ability to capture the increasing heterogeneity in urban lifestyles, new tendencies in mobility behavior, and the environmental impacts of land-use and transport policies at a finer spatial resolution (Hunt et al. [2008], Wagner and Wegener [2007], Acheampong and Silva [2015]). Additionally, the dynamic nature of micro-simulation models makes it possible to trace model components (e.g., individuals, households, jobs, and dwellings) over time, allowing for detailed observation of the processes of change that cannot be achieved with other types of models (Pagliara and Wilson [2010]).

Our agent-based microsimulation model construction is based on the construction of the model developed by McArthur et al. [2010]. McArthur et al. [2010] 's model is an agent-based microsimulation model that simultaneously deals with commuting and migration, involving two towns populated by a synthetic society of agents based on Norwegian statistical data. It follows a neoclassical style, where agents aim to maximize their utility function rather than simply following a predefined set of behavioral rules commonly seen in standard agent-based computational approaches (ACE) (Epstein [1999], Tesfatsion [2003]). The model enables the exploration of the relative influence of various factors in the adjustment process, as well as providing insights into when and why persistent disparities in unemployment arise.

Our agent-based microsimulation model is a substantial extension of the model in McArthur et al. [2010]. We have advanced the theory in that paper by including additional mechanisms to the model. For instance, our model considers a more comprehensive range of factors, particularly regarding geography. We have considered a spatial configuration consisting of 12 zones/towns within the region, which offers a more realistic representation than their model, which only included two zones. While McArthur et al. [2010]'s focus was solely on the distance between the two zones without considering other geographical aspects, our model incorporates various spatial structure characteristics such as changes in the road transportation infrastructure, the compactness of the system of towns in the geography, the clustering of local and basic sector jobs, and where the central business district is located.

The main contribution of our model is incorporating the housing market in the spatial context, where spatial interaction decisions reflect the spatial distribution of jobs and households, as well as spatial disparities in wages and housing prices. Additionally, we have accounted for heterogeneity in the labor market by including three different types of workers in our model. A comprehensive understanding of the model can be found in papers 2, 3, and 4 within this thesis, where detailed analyses are provided.

We have incorporated concepts from McArthur et al. [2014] spatial equilibrium model, which aimed to analyze the impact of changes in transportation networks and job distribution on rural depopulation in the western region of Norway. A detailed explanation of this model can be found in Section 4. Inspired by McArthur et al. [2014]'s work, our model incorporates a basic sector and a local sector. Also, within our geographic context, we have defined the Central Business District (CBD) following the insights provided by the aforementioned model.

Our agent-based microsimulation model offers some advantages. One advantage is the flexibility in scenario testing by manipulating various demographic factors and observing their impacts on the system. Additionally, our agent-based model can overcome limitations in existing data. The model can fill gaps or represent specific characteristics or behaviors of interest by generating synthetic populations. This enables a more comprehensive analysis of complex systems and provides insights that may not be possible with empirical data alone.

The model can explore scenarios beyond what has been observed in reality or are challenging to observe directly. By creating alternative conditions, researchers can investigate the behavior and interactions of agents under different circumstances. This expands the range of possible analyses and contributes to a deeper understanding of the system dynamics.

The level of control in these models enables us to determine the causal relationship between modifications and outcomes accurately. When a change is introduced to the model, any resulting changes in outcomes can be confidently attributed to that specific modification because no external factors or variables affect the system's functioning.

Our theoretical agent-based microsimulation model has plausible potential for future empirical life studies. In principle, it is conceivable to execute the model for a specific geography, generating agents based on real population data, thereby creating a foundation for undertaking empirical life studies. However, this exciting prospect remains the next phase for the model's development. At this stage, our focus was on exploring the effects that can be achieved through this type of agent-based stimulation. While running simulations for larger populations may present challenges in terms of running time, leveraging parallel processing techniques makes it feasible to handle such data-intensive scenarios.

6 Summary

Integrated land-use/transport models have a rich history spanning six decades. This review discusses the LUTI modeling frameworks and the modeling methodologies that have been applied over the years. To classify LUTI models, the categorization proposed by Iacono et al. [2008] is adopted : spatial interaction/gravity-based modeling, econometric modeling, and microsimulation/other computer-based modeling.

Spatial Interaction/Gravity models emerged by combining the Lowry model (Lowry [1964]) and the four-step model (Mitchell and Rapkin [1954]), and were referred to as "Large-scale" models in the literature. The second category of LUTI models, referred to as Econometric models, has further enhanced the price mechanism in urban formation. This is achieved by incorporating microeconomic theories such as bid-rent theory (Alonso [1964]) and random utility theory (McFadden [1977]) into the models. Some of these models, based on a general equilibrium framework, are recognized as an expansion of computable general equilibrium (CGE) models (Taylor and Black [1974]), which were originally developed for analyzing urban space formation.

In the early 1990s, New Economic Geography (NEG) emerged as a theory explaining the emergence of large agglomerations through increasing returns to scale and transportation costs, making a significant impact on the field of spatial economics. Krugman [1991] was among the pioneers who recognized the need to study the spatial pattern of production and consumption within a general equilibrium framework. He advocated for abandoning the assumption of perfect competition and constant returns to scale to effectively explain the agglomeration of economic activity. Building upon Krugman's work, multiregional input-output models exhibiting characteristics of NEG models are now referred to as Spatial Computable General Equilibrium (SCGE) models, although the term CGE originally had a broader meaning.

Microsimulation models, collectively known as "microsimulation," began to evolve in the early 1990s. These models encompassed agent-based models, cell-based models for land use change, and multi-agent models for urban modeling. As the 2000s began, researchers started developing comprehensive urban microsimulation models capable of capturing population dynamics and the urban environment.

One notable model that serves as the foundation for our work is the spatial equilibrium model formulated by McArthur et al. [2014]. Their objective was to strike a balance between Large-scale models and SCGE models. To achieve this, they constructed a spatial equilibrium model that departed from standard SCGE models by incorporating intraregional commuting and shopping patterns, which are typically associated with large-scale models.

References

Ransford A Acheampong and Elisabete A Silva. Land use–transport interaction modeling: A review of the literature and future research directions. *Journal of Transport and Land use*, 8 (3):11–38, 2015.

William Alonso. *Location and land use: toward a general theory of land rent*. Harvard university press, 1964.

K Amano, T Toda, and H Abe. A hierarchical urban model and its application to the osaka metropolitan area. In *A paper presented to the 23 rd European Congress of Regional Science Association held in Poitier, France*, 1983.

Alex Anas. *Residential location markets and urban transportation. economic theory, econometrics and policy analysis with discrete choice models*. Number Monograph. 1982.

Alex Anas and Richard J Arnott. The chicago prototype housing market model with tenure choice and its policy applications. *Journal of Housing Research*, pages 23–90, 1994.

Alex Anas and Yu Liu. A regional economy, land use, and transportation model (relu-tran©): formulation, algorithm design, and testing. *Journal of Regional Science*, 47(3):415–455, 2007.

Kenneth Joseph Arrow, Frank Hahn, et al. General competitive analysis. 1971.

Michael Balmer, Kay W Axhausen, and Kai Nagel. Agent-based demand-modeling framework for large-scale microsimulations. *Transportation Research Record*, 1985(1):125–134, 2006.

Michael Batty. Progress, success, and failure in urban modelling. *Environment and planning A*, 11(8):863–878, 1979.

Moshe Ben-Akivai, John L Bowman, and Dinesh Gopinath. Travel demand model system for the information era. *Transportation*, 23:241–266, 1996.

Brian JL Berry and William L Garrison. A note on central place theory and the range of a good. *Economic Geography*, 34(4):304–311, 1958.

Michel Bierlaire, Andrè De Palma, Ricardo Hurtubia, and Paul Waddell. *Integrated transport and land use modeling for sustainable cities*. Number BOOK. EPFL Press, 2015.

David E Boyce. Renaissance of large-scale models. *Papers in Regional Science*, 65(1):1–10, 1988.

A Brandsma, O Ivanova, and D Kancs. Rhomolo, a dynamic spatial general equilibrium model. 19th international input-output conference. *Alexandria, Virginia, USA*, 2011.

Johannes Bröcker. Operational spatial computable general equilibrium modeling. *The Annals of Regional Science*, 32:367–387, 1998.

Johannes Bröcker and Jean Mercenier. General equilibrium models for transportation economics. In *A handbook of transport economics*. Edward Elgar Publishing, 2011.

J Broecker, R Meyer, N Schneekloth, C Schuermann, K Spiekermann, and M Wegener. Modelling the socio-economic and spatial impacts of eu transport policy deliverable d6 of iason (integrated appraisal of spatial economic and network effects of transport investments and policies). *Kiel, Christian Albrechts University of Kiel*, 2004.

John F Brotchie, John W Dickey, and Ron Sharpe. Lecture notes in economics and mathematical systems, 1980.

Ron N Buliung and Pavlos S Kanaroglou. Activity–travel behaviour research: conceptual issues, state of the art, and emerging perspectives on behavioural analysis and simulation modelling. *Transport Reviews*, 27(2):151–187, 2007.

Roberta Capello. *Regional economics*. Routledge, 2015.

Sonny Conder and Keith Lawton. Alternative futures for integrated transportation and land use models contrasted with trend-delphi models: Portland oregon metro results. *Transportation research record*, 1805(1):99–107, 2002.

Michael C Daly. An approximation to a geographical multiplier. *The Economic Journal*, pages 248–258, 1940.

Juan de Dios Ortúzar and Luis G Willumsen. *Modelling transport*. John wiley & sons, 2011.

Tomás De la Barra. *Integrated land use and transport modelling. Decision chains and hierarchies.* Number 12. 1989.

Gerard Debreu. *Theory of value: An axiomatic analysis of economic equilibrium*, volume 17. Yale University Press, 1959.

Avinash K Dixit and Joseph E Stiglitz. Monopolistic competition and optimum product diversity. *The American economic review*, 67(3):297–308, 1977.

Xiaojing Dong, Moshe E Ben-Akiva, John L Bowman, and Joan L Walker. Moving from trip-based to activity-based measures of accessibility. *Transportation Research Part A: policy and practice*, 40(2):163–180, 2006.

Marcial Echenique. Econometric models of land use and transportation. In *Handbook of transport geography and spatial systems*, volume 5, pages 185–202. Emerald Group Publishing Limited, 2004.

Marcial H Echenique, Anthony DJ Flowerdew, John Douglas Hunt, Timothy R Mayo, Ian J Skidmore, and David C Simmonds. The meplan models of bilbao, leeds and dortmund. *Transport reviews*, 10(4):309–322, 1990.

Kent Eliasson, Urban Lindgren, and Olle Westerlund. Geographical labour mobility: migration or commuting? *Regional studies*, 37(8):827–837, 2003.

PT Ellsworth. Interregional and international trade, 1933.

Joshua M Epstein. Agent-based computational models and generative social science. *Complexity*, 4(5):41–60, 1999.

Bilal Farooq and Eric J Miller. Towards integrated land use and transportation: A dynamic disequilibrium based microsimulation framework for built space markets. *Transportation research part A: policy and practice*, 46(7):1030–1053, 2012.

H Floor and T De Jong. Testing a disaggregated residential location model with external zones in the amersfoort region. *Environment and Planning A*, 13(12):1499–1514, 1981.

Bent Flyvbjerg. Public planning of mega-projects: overestimation of demand and underestimation of costs. *Decision-making on Mega-projects: Cost-benefit analysis, planning, and innovation*, pages 120–44, 2008.

Masahisa Fujita, Paul R Krugman, and Anthony Venables. *The spatial economy: Cities, regions, and international trade*. MIT press, 2001.

P Geraldes, MH Echenique, and IN Williams. A spatial economic model for bilbao. In *Proceedings of the PTRC Summer Annual Meeting*, pages 75–94. PTRC Education and Research Services Ltd 110 Strand, London WC2, 1978.

Karst T Geurs and Bert Van Wee. Accessibility evaluation of land-use and transport strategies: review and research directions. *Journal of Transport geography*, 12(2):127–140, 2004.

Karst T Geurs, Michiel de Bok, and Barry Zondag. Accessibility benefi ts of integrated land use and public transport policy plans in the netherlands. In *Accessibility analysis and transport planning*, pages 135–153. Edward Elgar Publishing, 2012.

Arnstein Gjestland, Inge Thorsen, and Jan Ubøe. Some aspects of the intraregional spatial distribution of local sector activities. *The Annals of Regional Science*, 40(3):559–582, 2006.

William Goldner. The lowry model heritage. *Journal of the American Institute of Planners*, 37 (2):100–110, 1971.

OPUS User Guide. The open platform for urban simulation and urbansim version 4.3. *University of California Berkeley and University of Washington*, 2011.

G Haag. Housing 2-a master equation approach and services 2-a master equation approach for labour mobility. *Urban Dynamics: Designing an Integrated Model, Routledge, London*, pages 184–236, 1990.

Susan L Handy. Regional versus local accessibility: neo-traditional development and its implications for non-work travel. *Built Environment (1978-)*, pages 253–267, 1992.

Walter G Hansen. How accessibility shapes land use. *Journal of the American Institute of planners*, 25(2):73–76, 1959.

Wiljar Hansen and Olga Ivanova. Wider economic benefits in transport appraisal, a scge-model approach with application to a proposed norwegian road infrastructure project. In *European Transport Conference 2012Association for European Transport (AET) Transportation Research Board*, 2012.

Wiljar Hansen and Bjørn Gjerde Johansen. Regional repercussions of new transport infrastructure investments: An scge model analysis of wider economic impacts. *Research in transportation economics*, 63:38–49, 2017.

Susan Hanson. The context of urban travel. *The geography of urban transportation*, pages 3–29, 2004.

Arnold C Harberger. The measurement of waste. *The American Economic Review*, pages 58–76, 1964.

James W Henderson and Beck A Taylor. Rural isolation and the availability of hospital services. *Journal of Rural Studies*, 19(3):363–372, 2003.

C Heyndrickx, O Ivanova, A VAN STEENBERGEN, I Mayeres, B Hamaide, T Eraly, and F Witlox. Development of an integrated spatio-economic-ecological model methodology for the analysis of sustainability policy. *Transport & Mobility Leuven*, 2009.

Christophe Heyndrickx, Olaf Koops, and Olga Ivanova. The tiger model: Application of detailed passenger and freight transport in a regional cge setting. 2011.

Alan J Horowitz. Lowry-type land use models. In *Handbook of transport geography and spatial systems*, volume 5, pages 167–183. Emerald Group Publishing Limited, 2004.

John D Hunt and John E Abraham. Design and implementation of pecas: A generalised system for allocating economic production, exchange and consumption quantities. In *Integrated Land-Use and Transportation Models*, pages 253–273. Emerald Group Publishing Limited, 2005.

John D Hunt, David S Kriger, and Eric J Miller. Current operational urban land-use–transport modelling frameworks: A review. *Transport reviews*, 25(3):329–376, 2005.

John Douglas Hunt and John E Abraham. Design and application of the pecas land use modelling system. In *8th Computers in Urban Planning and Urban Management Conference, Sendai, Japan*, 2003.

John Douglas Hunt, John E Abraham, Dimantha De Silva, Ming Zhong, Jamie Bridges, and J Mysko. Developing and applying a parcel-level simulation of developer actions in baltimore. In *Transportation Research Board 87th Annual Meeting*, number 08-2593, 2008.

Michael Iacono, David Levinson, and Ahmed El-Geneidy. Models of transportation and land use change: A guide to the territory. *Journal of Planning Literature*, 22(4):323–340, 2008.

Olga Ivanova, Christophe Heyndrickx, Karel Spitaels, Lori Tavasszy, Walter Manshanden, Maaike Snelder, and Olaf Koops. Raem: version 3.0. *Transport Mobility Leuven, Leuven*, 2007.

Sergio R Jara-Diaz. On the relation between users'benefits and the economic effects of transportation activities. *Journal of regional science*, 26(2):379–391, 1986.

Yoshitsugu Kanemoto and Koichi Mera. General equilibrium analysis of the benefits of large transportation improvements. *Regional Science and Urban Economics*, 15(3):343–363, 1985.

Eric Damian Kelly. The transportation land-use link. *Journal of Planning Literature*, 9(2): 128–145, 1994.

Masanobu Kii, Hitomi Nakanishi, Kazuki Nakamura, and Kenji Doi. Transportation and spatial development: An overview and a future direction. *Transport Policy*, 49:148–158, 2016.

Ryuichi Kitamura, Eric I Pas, Clarisse V Lula, T Keith Lawton, and Paul E Benson. The sequenced activity mobility simulator (sams): an integrated approach to modeling transportation, land use and air quality. *Transportation*, 23:267–291, 1996.

Carl Koopmans and Jan Oosterhaven. Scge modelling in cost-benefit analysis: The dutch experience. *Research in Transportation Economics*, 31(1):29–36, 2011.

Kevin J Krizek. Neighborhood services, trip purpose, and tour-based travel. *Transportation*, 30:387–410, 2003.

Paul Krugman. Increasing returns and economic geography. *Journal of political economy*, 99 (3):483–499, 1991.

Paul Krugman. *Geography and trade*. MIT press, 1992.

Paul Krugman and Anthony J Venables. Globalization and the inequality of nations. *The quarterly journal of economics*, 110(4):857–880, 1995.

Paul R Krugman. Intraindustry specialization and the gains from trade. *Journal of political Economy*, 89(5):959–973, 1981.

Douglass B Lee. Retrospective on large-scale urban models. *Journal of the American Planning Association*, 60(1):35–40, 1994.

Douglass B Lee Jr. Requiem for large-scale models. *Journal of the American Institute of planners*, 39(3):163–178, 1973.

Ira S Lowry. A model of metropolis. Technical report, Rand Corp Santa Monica Calif, 1964.

Emma Lundholm. Interregional migration propensity and labour market size in sweden, 1970–2001. *Regional studies*, 44(4):455–464, 2010.

Lars Lundqvist. *Analysing the impacts of energy factors on urban form*. Research Group for Urban and Regional Planning, Department of Mathematics ..., 1984.

Roger L Mackett. Leeds integrated land-use transport model (lilt). Technical report, 1983.

Roger L Mackett. The systematic application of the lilt model to dortmund, leeds and tokyo. *Transport Reviews*, 10(4):323–338, 1990.

Roger L Mackett. Lilt and meplan: A comparative analysis of land-use and transport policies for leeds. *Transport Reviews*, 11(2):131–154, 1991.

Francisco Martinez. Mussa: land use model for santiago city. *Transportation Research Record*, 1552(1):126–134, 1996.

Francisco J Martinez. The bid—choice land-use model: an integrated economic framework. *Environment and Planning A*, 24(6):871–885, 1992.

David Philip McArthur, Inge Thorsen, and Jan Ubøe. A micro-simulation approach to modelling spatial unemployment disparities. *Growth and Change*, 41(3):374–402, 2010.

David Philip McArthur, Inge Thorsen, and Jan Ubøe. Employment, transport infrastructure, and rural depopulation: a new spatial equilibrium model. *Environment and Planning A*, 46 (7):1652–1665, 2014.

David Philip McArthur, Inge Thorsen, and Jan Ubøe. Some consequences of ignoring relocations in the cost–benefit analysis of transportation infrastructure investments. *Innovations in Urban and Regional Systems: Contributions from GIS&T, Spatial Analysis and Location Modeling*, pages 137–164, 2020.

Daniel McFadden. Modelling the choice of residential location. 1977.

Peter G McGregor, Eric P McVittie, J Kim Swales, and Ya Ping Yin. The neoclassical economic base multiplier. *Journal of Regional Science*, 40(1):1–31, 2000.

Michael G McNally. The activity-based approach. in: Handbook of transport modelling. 2000.

Robert B Mitchell and Chester Rapkin. *Urban traffic: A function of land use*. Columbia University Press, 1954.

Kazuaki Miyamoto and Keiichi Kitazume. A land-use model based on random utility rent-bidding analysis rurban. In *TRANSPORT POLICY, MANAGEMENT & TECHNOLOGY TOWARDS 2001: SELECTED PROCEEDINGS OF THE FIFTH WORLD CONFERENCE ON TRANSPORT RESEARCH*, volume 4, 1989.

Rolf Moeckel, Carlos Llorca Garcia, Ana T Moreno Chou, and Matthew Bediako Okrah. Trends in integrated land-use/transport modeling. *Journal of Transport and Land Use*, 11(1):463–476, 2018.

Rolf Moekel, Klaus Spiekermann, Carsten Schürmann, and Michael Wegener. Microsimulation of land use. *International Journal of Urban Sciences*, 7(1):14–31, 2003.

Gunnar Myrdal and Paul Sitohang. Economic theory and under-developed regions. 1957.

Hideo Nakamura and Yoshitsugu Hayashi. Transportation-land use model for evaluation of traffic facilities. In *Transport Research for Social and Economic Progress. Proceedings of the Second World Conference on Transport ResearchUnited Kingdom GovernmentOrganisation for Economic Cooperation and DevelopmentEuropean Conference of Ministers of Transport*, 1981.

Hideo Nakamura, Yoshitsugu Hayashi, and Kazuaki Miyamoto. A land use-transport model for metropolitan areas. *Papers in Regional Science*, 51(1):43–63, 1983.

Jan Oosterhaven, Jan-Egbert Sturm, and Peter Zwaneveld. *Naar een theoretische onderbouwde aanpak van voorwaartse economische effecten*. TNO-INRO, 1998.

Jan Oosterhaven, Thijs Knaap, Cees Ruijgrok, and L Tavassy. On the development of raem: The dutch spatial general equilibrium model and its first application to a new railway link. In *41th Congress of the European Regional Science Association, Zagreb, August*, volume 29, 2001.

Guy H Orcutt. Microanalysis of socioeconomic systems. 1961.

Francesca Pagliara and Alan Wilson. The state-of-the-art in building residential location models. In *Residential location choice: Models and applications*, pages 1–20. Springer, 2010.

John B Parr. Outmigration and the depressed area problem. *Land economics*, 42(2):149–159, 1966.

François Perroux. *Note sur la notion de" pôle de croissance"*. Éditeur inconnu, 1955.

Stephen H Putman. Preliminary results from an integrated transportation and land use models package. *Transportation*, 3(3):193–224, 1974.

Soora Rasouli and Harry Timmermans. Activity-based models of travel demand: promises, progress and prospects. *International Journal of Urban Sciences*, 18(1):31–60, 2014.

Wilfred W Recker. A bridge between travel demand modeling and activity-based travel analysis. *Transportation Research Part B: Methodological*, 35(5):481–506, 2001.

Harry W Richardson. Input-output and economic base multipliers: Looking backward and forward. *Journal of Regional science*, 25(4):607–661, 1985.

SACTRA. Transport and the economy, report by standing advisory committee on trunk road assessment (sactra). *Department for Transport*, 1999.

Paul Salvini and Eric J Miller. Ilute: An operational prototype of a comprehensive microsimulation model of urban systems. *Networks and spatial economics*, 5:217–234, 2005.

Paul A Samuelson. The transfer problem and transport costs, ii: Analysis of effects of trade impediments. *The Economic Journal*, 64(254):264–289, 1954.

Ashish Sen and Tony E Smith. *Gravity models of spatial interaction behavior*. Springer Science & Business Media, 2012.

Yoram Shiftan. The use of activity-based modeling to analyze the effect of land-use policies on travel behavior. *Annals of Regional Science*, 42(1), 2008.

David Simmonds. The objectives and design of a new land-use modelling package: Delta. *Regional science in business*, pages 159–188, 2001.

David Simmonds and Ben Still. Delta/start: adding land use analysis to integrated transport models. In *World Transport Research: Selected Proceedings of the 8th World Conference on Transport ResearchWorld Conference on Transport Research Society*, number Volume 4, 1999.

Samuel A Stouffer. Intervening opportunities: a theory relating mobility and distance. *American sociological review*, 5(6):845–867, 1940.

Dirk Strauch, Rolf Moeckel, Michael Wegener, Jürgen Gräfe, Heike Mühlhans, Guido Rindsfüser, and Klaus-J Beckmann. Linking transport and land use planning: The microscopic dynamic simulation model ilumass. In *Geodynamics*, pages 319–336. CRC Press, 2004.

Marcus Sundberg. *Spatial computable general equilibrium modelling: static and dynamic approaches.* PhD thesis, KTH, 2005.

LA Tavasszy, MJPM Thissen, and Jan Oosterhaven. Challenges in the application of spatial computable general equilibrium models for transport appraisal. *Research in Transportation Economics*, 31(1):12–18, 2011.

Lóri Tavasszy, Mark Thissen, Jos Muskens, and Jan Oosterhaven. Pitfalls and solutions in the application of spatial computable general equilibrium models for transport appraisal. 2002.

Lance Taylor and Stephen L Black. Practical general equilibrium estimation of resource pulls under trade liberalization. *Journal of international Economics*, 4(1):37–58, 1974.

Marco Te Brömmelstroet, Peter Pelzer, and Stan Geertman. Forty years after lee's requiem: are we beyond the seven sins? *Environment and Planning B: Planning and Design*, 41(3): 381–387, 2014.

Leigh Tesfatsion. Agent-based computational economics: modeling economies as complex adaptive systems. *Information sciences*, 149(4):262–268, 2003.

Charles M Tiebout. The community economic base study. *(No Title)*, 1962.

George I Treyz. Symposium on multiregional forecasting and policy simulation models: Design of a multiregional policy analysis model. *Journal of Regional Science*, 20(2):191–206, 1980.

George I Treyz, Dan S Rickman, and Gang Shao. The remi economic-demographic forecasting and simulation model. *International Regional Science Review*, 14(3):221–253, 1991.

Maarten Van Ham and Pieter Hooimeijer. Regional differences in spatial flexibility: long commutes and job related migration intentions in the netherlands. *Applied spatial analysis and policy*, 2:129–146, 2009.

Jan Veldhuisen, Harry Timmermans, and Loek Kapoen. Ramblas: a regional planning model based on the microsimulation of daily activity travel patterns. *Environment and Planning A*, 32(3):427–443, 2000.

Roger Vickerman. Recent evolution of research into the wider economic benefit of transport infrastructure investments. 2008.

Paul Waddell. A behavioral simulation model for metropolitan policy analysis and planning: residential location and housing market components of urbansim. *Environment and planning B: planning and design*, 27(2):247–263, 2000.

Paul Waddell. Urbansim: Modeling urban development for land use, transportation, and environmental planning. *Journal of the American planning association*, 68(3):297–314, 2002.

Paul Waddell and Gudmundur F Ulfarsson. Introduction to urban simulation: Design and development of operational models. In *Handbook of transport geography and spatial systems*, volume 5, pages 203–236. Emerald Group Publishing Limited, 2004.

Paul Waddell, Alan Borning, Hana Ševčíková, and David Socha. Opus (the open platform for urban simulation) and urbansim 4. In *Proceedings of the 2006 international conference on Digital government research*, pages 360–361, 2006.

Paul Waddell, Liming Wang, Billy Charlton, and Aksel Olsen. Microsimulating parcel-level land use and activity-based travel: Development of a prototype application in san francisco. *Journal of Transport and Land Use*, 3(2):65–84, 2010.

Peter Wagner and Michael Wegener. Urban land use, transport and environment models: Experiences with an integrated microscopic approach. *DisP-the planning review*, 43(170): 45–56, 2007.

FV Webster, Philip H Bly, and Neil J Paulley. *Urban land use and transport interaction; policies and models*. 1988.

Michael Wegener. Modeling urban decline: A multilevel economic-demographic model for the dortmund region. *International Regional Science Review*, 7(2):217–241, 1982.

Michael Wegener. The dortmund housing market model: a monte carlo simulation of a regional housing market. In *Microeconomic models of housing markets*, pages 144–191. Springer, 1985.

Michael Wegener. Reduction of co 2 emissions of transport by reorganisation of urban activities. *Transport, land-use and the environment*, pages 103–124, 1996.

Michael Wegener. Overview of land use transport models. In *Handbook of transport geography and spatial systems*, volume 5, pages 127–146. Emerald Group Publishing Limited, 2004.

Michael Wegener. Transport in spatial models of economic development. In *A handbook of transport economics*. Edward Elgar Publishing, 2011.

Michael Wegener and Franz Fürst. Land-use transport interaction: State of the art. *Berichte aus dem Institut für Raumplanung*, 46, 1999.

Morten Welde and Eivind Tveter. The wider local impacts of new roads: A case study of 10 projects. *Transport policy*, 115:164–180, 2022.

Jing Zhang, Fangjian Chen, and X-X Yuan. Comparison of cost and schedule performance of large public projects under p3 and traditional delivery models: A canadian study. *Construction management and economics*, 38(8):739–755, 2020.

Barry Zondag, Michiel de Bok, Karst T Geurs, and Eric Molenwijk. Accessibility modeling and evaluation: The tigris xl land-use and transport interaction model for the netherlands. *Computers, environment and urban systems*, 49:115–125, 2015.

An agent-based approach to study spatial structure effects on estimated distance deterrence in commuting.

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Abstract

We provide an experimental design to study how estimates of the distance deterrence parameter in a standard doubly-constrained gravity model respond to different patterns of spatial structure. The design is defined for an agent-based simulation framework that simultaneously consider the response on commuting and migration to changes in the spatial structure, accounting for labour and housing market issues. The agents are equipped with a bounded rationality utility function and are expected to maximize their utilities with regard to their wage net of commuting costs, and the value of their house. We study how the estimates of the distance deterrence parameter respond to where the central business district is located, to the clustering of local and basic sector jobs, to changes in the road transportation network, and to the compactness in the system of towns in the geography.

Keywords: commuting, spatial structure, distance deterrence parameter, agent-based modelling

JEL-codes: J61, R23, R41

1 Introduction

According to Tobler's first law of geography, "everything is related to everything else, but near things are more related than distant things"(Tobler 1970). This is reflected by the distance deterrence parameter in standard spatial interaction models, and estimates of this parameter are

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sometimes given a behavioural explanation. There certainly is a behavioural element in explaining the estimates of the parameter, but the literature provides convincing evidence that the pure behavioural interpretation calls upon controlling for instance for spatial structure characteristics in the model formulation. Commuting is the form of spatial interaction to be considered in this paper, and gravity modeling is the standard device for estimation and predictions. Estimates of the distance deterrence parameter in general differ across countries and regions. This may of course reflect behavioural differences, but it may also reflect differences in the spatial structure.

Estimates of the distance deterrence parameter provide interesting information on spatial interaction per se. In addition, estimates are important for predicting how spatial interaction is affected by changes in characteristics of the spatial structure and the transportation network. How will a new road connection affect commuting, for a given spatial pattern of jobs and residents? This is of course a crucial question in a cost-benefit evaluation of the investments in road infrastructure, and the answer calls for estimates of the changes in commuting times as well as for the distance deterrence parameter. If data on commuting flows are missing for the region, then the possibility should be considered to use estimates from some other region. This raises the issue of transferability of such estimates over time and space (see for instance McArthur et al., 2011). What kind of other region should be considered for estimates to be least possible biased? Is the parameter estimate autonomous to the change in transportation network?

Our discussion provides suggestions of how to modify the standard gravity model in order to avoid omitted variable bias and to provide more reliable predictions. Hence, the main ambition of this paper is both to contribute to a firm understanding and interpretation of the distance deterrence parameter following from a standard spatial interaction model, and to provide useful input for the evaluation and formulation of spatial interaction models.

To our knowledge, there are no empirical studies that systematically examine how different aspects of spatial structure affect the estimates of the distance deterrence parameter in commuting. We do neither perform an empirical study, but rather use controlled experiments to address the issues. To be more precise, we are using an agent-based approach, that is a microsimulation modelling approach. This allows for experiments that can hardly be made in real world situations, like considering effects of a partial change in a covariate. Hence, we are able to avoid complex causality issues and endogeneity problems. The agent-based approach is something in between pure theoretical analysis and empirical analysis. It offers the possibility of controlled experiments, accounting for a lot more details and complexity than an analytical approach. This paper demonstrates the potential of such an approach to study how a specific economic state results from complex interactions between the agents in a synthetic population of households.

The number of experiments that are run has been limited by the computing time, as each data point in the figures to be presented on average called for around 5 hours of computing time. The coding has been done in Mathematica. Other programming languages may run the experiments many times faster, and we are sure that more advanced programming in addition has the potential of speeding up the computations considerably. Our ambitions for this paper are twofold. One is to demonstrate the potential of the agent-based modelling in reaching a better understanding of how the outcome of complex interactions can explain and predict aggregate patterns in an economy. Due to the limitations of computer capacity, we had to run the agent-based experiments for a relatively small geography, with respect to the number of agents involved. With more resources available for computing and computer capacity, we are sure that this approach has the potential of analysing urban and regional systems of any size, within a reasonable time perspective. For our second ambition, however, the computing capacity limitation was not a significant problem. We think that the experiments provide interesting results related to spatial interaction modelling, as well as important and non-trivial insight into the relationship between spatial interaction and characteristics of the spatial structure.

We make no attempts to modify the standard doubly-constrained gravity model to account for characteristics of spatial structure. The basic model is presented in Section 2, including a review of literature discussing the distance deterrence parameter. Section 3 gives a presentation of the agent-based modelling framework. This involves the geography, represented by the spatial configuration of towns, the demographics, the preferences of the agents, the spatial labour market interaction, and the supply and demand for housing. First, a benchmark scenario is defined in Section 4, before the results are presented in Section 5. In Section 6, we discuss issues related to model performance and how sensitive predicted commuting flows are to the value of the distance deterrence parameter. Finally, concluding remarks are offered in Section 7.

2 The distance deterrence parameter in a standard gravity model of commuting

In gravity models of trip distribution problems, spatial interaction is explained by the distance between an origin and a destination, by the generativity of origins and by the attraction of destinations. For commuting, the generativity of origins is in general defined in terms of the number of workers residing in the zone, while the attraction of a destinations is measured by the local number of jobs. A standard formulation of a doubly constrained gravity model is:

$$T_{ij} = A_i O_i B_j D_j \exp(-\beta d_{ij}) \tag{1}$$

$$A_i = \left[\sum_j B_j D_j \exp(-\beta d_{ij}) \right]^{-1} \tag{2}$$

$$B_j = \left[\sum_i A_i O_i \exp(-\beta d_{ij}) \right]^{-1} \tag{3}$$

where:

T_{ij} is the estimated number of commuters from origin i to destination j, $i, j = 1, ..., n$

O_i is the observed number of trips originating from zone $i = 1, ..., n$

D_j is the observed number of trips destinating in zone $j = 1, ..., n$

d_{ij} is travelling time by car, from origin i to destination j; $i, j = 1, ..., n$

β is a distance deterrence parameter. A_i and B_j are the balancing factors that ensure the fulfillment of the marginal total constraints for this trip distribution problem; $\sum_j T_{ij} = O_i$ and $\sum_i T_{ij} = D_j$. For a discussion of the theoretical foundation of this model, see for example Erlander and Stewart (1990) or Sen and Smith (1995). The doubly constrained gravity model is equivalent to the multinomial logit model, see for example Anas (1983, 1984) for more details on the relationship between these two modeling traditions. This means that the gravity model can be derived from stochastic utility theory, in addition to approaches dominated by the macro-oriented tradition that is inspired by social physics and based on the entropy concept.

As pointed out by for example Persyn and Torfs (2016), an unconstrained version of the model is a bit naive in a commuting context, since it ignores the possibility that the interaction between two zones may be influenced by characteristics of other zones. The introduction of the balancing factors means that many relevant characteristics of the spatial structure are accounted for. Sometimes, a hybrid model may be appropriate, where only some of the zones are constrained, at either the origin or the destination side of the interaction (Wilson 2010).

d_{ij} can be interpreted as a generalized measure, involving both expenses and time costs. The experiments in this paper are not specific on the value of time involved in commuting, but time costs can be seen as forgone earnings. Our estimate of commuting costs per unit of distance represent the generalized costs of commuting one more kilometer per day. Hence, the estimate reflects the opportunity costs of a longer journey to work, but we assume that there is no inconvenience costs involved, in addition to the expenses and the value of the time spent on the journey.

The gravity model for commuting flows can be derived from an entropy maximizing procedure, where one of the constraints defines an upper limit on total transportation costs. The distance deterrence parameter can be interpreted to measure the impact on commuting flows of a marginal release in the cost constraint. As pointed out by Wilson (2010), a reduction in the total expenditures on travel is equivalent to an increased value of the β parameter. A straightforward derivation of the gravity model from entropy maximization leads to a negative exponential impedance function, $\exp(-\beta d_{ij})$. However, if the cost function is formulated by the log values of traveling costs, the resulting distance deterrence effect will be represented by a power function, $d_{ij}^{-\beta}$, see for instance Wilson (2010). Wilson (2010) indicate that a power function representation of distance may be appropriate if there are many long trips, in an interurban geography. There is also support in the literature that the choice of a deterrence function is essentially a pragmatic one (see for example Nijkamp and Reggiani 1992).

The interpretation of the distance deterrence parameter has been profoundly discussed in the literature, in particular in the late 70s and in the 80s. It was demonstrated how leaving out relevant characteristics of spatial structure may result in biased parameter estimates, that will then not be representing unbiased behavioral estimates of how variations in distance affect spatial interaction decisions. According to Tiefelsdorf (2003), this problem of interaction modeling did not receive much attention in the literature in the 90s, "despite the fact that no satisfactory solution has been found". It appears to us that this is still an understudied area of research.

Theoretical and empirical contributions to the debate can be found in Cliff et al. (1974), Curry et al. (1975), Sheppard (1978, 1984), Fotheringham and Webber (1980), Fotheringham (1981, 1983a, 1983b, 1986), Ishikawa (1987), and Desta and Pigozzi (1991). Lo (1992) points out that this literature relied heavily on the migration context. In a commuting context, it is well known that the balancing factors in a doubly-constrained gravity model formulation capture relevant characteristics of the spatial structure. However, as demonstrated by for example Gitlesen and Thorsen (1998, 2000), separate measures of spatial structure characteristics contribute significantly to explain commuting flows, also in doubly-constrained model formulations. Gitlesen and Thorsen (1998, 2000), for example, successfully incorporated into the model a so called Hansen measure of labour market accessibility, corresponding to the competing destinations model formulation of spatial interaction, that was developed by Fotheringham (1983a), see also Fotheringham (1986), and Pellegrini and Fotheringham (2002) for a review.

Some of this literature is also reviewed in Tiefelsdorf (2003), who in addition demonstrates how a proper model specification is of paramount importance in interaction modeling. Nævdal et al. (2002) account for spatial characteristics, such as the effect of intervening opportunities, in a network approach to explain and predict commuting flows. Accounting for relevant characteristics is of course important for producing unbiased parameter estimates, as well as for making reliable predictions, for instance on interregional transferability problems (see for instance McArthur et al. (2011)).

3 The agent-based modelling framework

The agent-based modelling approach has been used to study for example the impact of decentralized decision-making on the observed spatial patterns (Page, 1999; Batty, 2005; Irwin, 2010). According to Wilson (2010), we have a case of agent-based modelling when "the system of interest is populated by individual agents who are given (probabilistic) rules of behaviour". In this section, we explain how a population is generated, with a (random) diversity of preferences, and random demographic characteristics based on regularities observed in Norwegian statistical data. The microsimulations account for both the decision-making of the agents, and the functioning of the labour market and the housing market in the geography.

3.1 The geography

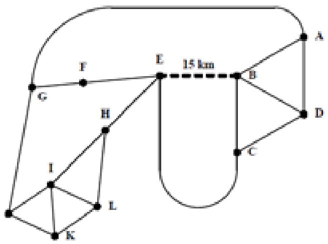


Figure 1: The spatial configuration of towns in the geography.

We consider a spatial configuration of 12 nodes, or towns, as illustrated in Figure 1. The towns A, B, C and D are located at one side of a topographical barrier, while the other towns are located at the same side as zone E, which hosts the central business district of the geography. The distances between the towns in the geography are given by the following matrix:

$$\begin{bmatrix}
0 & 15 & 30 & 15 & 75 & 75 & 65 & 85 & 100 & 90 & 100 & 100 \\
15 & 0 & 15 & 15 & 60 & 70 & 80 & 70 & 85 & 95 & 95 & 85 \\
30 & 15 & 0 & 15 & 45 & 55 & 65 & 55 & 70 & 80 & 80 & 70 \\
15 & 15 & 15 & 0 & 60 & 70 & 80 & 70 & 85 & 95 & 95 & 85 \\
75 & 60 & 45 & 60 & 0 & 10 & 20 & 10 & 25 & 35 & 35 & 25 \\
75 & 70 & 55 & 70 & 10 & 0 & 10 & 20 & 35 & 35 & 45 & 35 \\
65 & 80 & 65 & 80 & 20 & 10 & 0 & 30 & 35 & 25 & 35 & 45 \\
85 & 70 & 55 & 70 & 10 & 20 & 30 & 0 & 15 & 25 & 25 & 15 \\
100 & 85 & 70 & 85 & 25 & 35 & 35 & 15 & 0 & 10 & 10 & 10 \\
90 & 95 & 80 & 95 & 35 & 35 & 25 & 25 & 10 & 0 & 10 & 20 \\
100 & 95 & 80 & 95 & 35 & 45 & 35 & 25 & 10 & 10 & 0 & 10 \\
100 & 85 & 70 & 85 & 25 & 35 & 45 & 15 & 10 & 20 & 10 & 0
\end{bmatrix}$$

3.2 Demographics

Similar to McArthur et al. (2010, 2012), the initialization of the system is based on a number of fifteen years old utility maximizing agents, with given probabilities of being born in a specific town. They then interact for 300 years according to rules based on Norwegian statistical data, after which all the traces of the initial population are wiped out, and a population is made up that is representative for the Norwegian population. During one time-step (one month), agents can be born, marry, divorce, have children, apply for work, be retired, or die. We know the state of each agent at any time, represented by information like gender, age, marital status, spouse, father, mother, children, house(s), address, work location, income, wealth and utility parameters.

The rules in the model are basically the same as for the simple two-node system that was considered in McArthur et al. (2010, 2012). Any adult woman in the model can give birth with the probability of doing so being conditional on age and marital status. The sex of a child is determined randomly. If the woman is not married, the father is drawn randomly from the population of single men. Children are converted to adults when they reach the age of 15, and people retire at the age of 70. Adults can marry, divorce, have children and apply for work. Mortality rates are based on standard life insurance tables, using Gompertz-Makeham's law i.e. that the death intensity of a man of age x is given by the function:

$$\mu = a + bc^x \qquad \text{where} \qquad a = 0.9, b = 4.4 \cdot 10^{-5} \text{ and } c = 1.10154$$

Death rates of women are adjusted by a 3 year age correction. Single agents can get married with the probability being conditional on age, sex and previous marital status. Spouses are drawn from the population of single people, but there is a distance deterrence in marrying; the chances of marrying a person in another town is assumed to decline exponentially with distance:

$$\text{Max}\left[e^{-\sigma \cdot d}, 0.01\right]$$

Here, d is the distance between the towns and σ is a parameter controlling how quickly the probability declines with distance. When a couple marries, they move in together along with any children they already have. Divorce rates are conditional on age and sex.

3.3 Preferences

The life-time earnings is the relevant variable representing the consumption opportunities. In addition, the consumption opportunities depend on housing market transactions. Let V_i denote the life-time earnings of individual i, plus the current value of the house, minus the price of the house at the point in time when it was acquired. Hence, V_i is a measure of the income that is disposable for consumption in a life-time perspective. In addition, individuals are assumed to derive utility from housing consumption, represented by the size of the house, and no other attributes. Let H_i be the house size of household i, represented by the number of squared meters. This defines a utility function like the one underlying the Alonso-Muth model of land use and housing markets (Alonso, 1964 and Muth, 1969), and it is given by:

$$U_i(V, H) = V_i^{\alpha_i} H_i^{1-\alpha_i} \qquad 0 < \alpha_i < 1 \tag{4}$$

where α_i is the elasticity of the utility with respect to changes in life-time disposable income.

The housing market conditions do of course influence the development in the different towns. Assume for instance that a worker accepts a job offer from an employer in another town. Commuting and migration represent two alternative responses in terms of spatial interaction. The migration option involves finding a new house in another town, which means that housing prices and mechanisms in the housing market affect the decisions to migrate or not, and vice versa.

3.4 Employment, and spatial labour market interaction

The workers are assumed to be homogenous in terms of labour market qualifications. They apply for vacant jobs in the region if this contributes to a net gain in utility for the household. Job applicants are randomly selected for the vacant job positions, and those who are employed may stay in the job until they retire. If a worker accepts a job offer in another town, one option is to move to that town. For a married worker, this requires that the sum of utilities of the spouses is increased, accounting for changes in housing and other consumption. Alternatively, the worker will have to commute to the new job location. Unemployed agents receive an insurance payment.

There are two types of firms. The local sector firms firms are serving the local population, while the basic sector firms are serving demand in other regions and countries. Basic sector production is assumed to be exogenously given. In export-base theory, local sector employment is often assumed to be proportional to the local number of inhabitants. However, as argued and demonstrated in Gjestland et al. (2006), the density of local sector activities tends to be higher in the central business district (cbd) of a region. It is in particular customers in nearby towns who make their shopping in the cbd, as a result of comparing traveling cost to benefits in terms of lower prices and economies of scope in shopping. For towns located further from the cbd, the dominant part of the shopping takes place within the town. Hence, the local sector activities tend to be high in the cbd, low in suburban kind of towns, and close to the regional average in towns in a long distance from the cbd. Our agent-based modeling framework incorporates the model presented in Gjestland et al (2006) along this line of arguing. The model has been parameterized and applied in McArthur et al. (2014, 2020).

The wage rate is set higher in the cbd than in the other towns initially, due the hypothesis of agglomeration economies in the labour market. For the years to follow, wages are determined through a local Phillips curve style mechanism, opening for wage disparities across the towns, see McArthur et al. (2010). The wages are assumed to be the only source of income for employees, and there is an income tax, in addition to a fixed amount of money spent on for example taxes related to power, water supply etc, and other expenses that are considered to be necessary for a normally comfortable life.

3.5 The housing market

The housing market is one of the determinants of the migration/commuting tradeoff. Large spatial disparities in housing prices are, for instance, expected to contribute to reduce the probability of moving from an area with low housing prices to an area with high housing prices, pulling in the direction of commuting-based solutions in this direction. The local housing prices are endogenously determined in the model, responding to the balance between demand and supply in the local housing market.

3.5.1 Housing demand

The housing demand is represented by a bidding procedure. The bidding procedure uses first-price sealed bid auctions, in which all bidders submit their bids simultaneously, and the highest bid wins the auction. According to auction theory, see e.g. Krishna (2002), a Bayesian Nash equilibrium is obtained when bidder i has a valuation v_i and bids

$$\frac{N-1}{N}v_i,$$

where N is the number of bidders in the auction. The factor $\frac{N-1}{N}$ leads to significantly lower bids when N is small, and this effect appears to be crucial to get a reasonable price development in the housing market.

The factor is not meaningful if $N = 1$, and in our model we have instead used the factor

$\max[\frac{N-1}{N}, \frac{1}{2}]$ to take that into account. Anticipating that in real world auctions the number of bidders is not always very clear, we have used an adjustment

$$0.2 + 0.8 \max\left[\frac{N-1}{N}, \frac{1}{2}\right],$$

taking into account that that bidders may sometimes fear that slightly more people might be interested in bidding, and are hence placing a slightly higher bid. This reduces the strength of the factor to 80% of its original strength.

Who are the bidders in the auction? At each time-step the agents make a random check to see if they might be interested to join a pool of potential bidders, and join the pool if the check is successful. Which houses are for sale? Our model has a pool of houses for sale. At each time-step new houses might be added. The government builds new houses when there is sufficient demand, and house-owners makes a random check and if successful his or hers house is added to the pool. When a sale is successfully executed, the house is removed from the pool.

How do the agents value a house? All agents in the pool of potential bidders scan the pool of houses for sale in search of the house that provides them with the maximal utility. In their utility valuations they assume that houses can be bought for the quoted price, using the price per area unit in the previous period as a benchmark. They compare this utility to their current state of affairs, and joins a sub-pool of bidders for this particular property if they find that the new house would improve their position.

How is the auction carried out? For each house in the pool of houses for sale, the program constructs a subpool of bidders. If this sub-pool is non-empty, the program puts $N =$ number of bidders in the sub-pool. Each bidder draws a random number from a log-normal distribution with parameters μ and σ. To avoid wild outliers, σ must be rather small and in our computations we have used $\sigma = 0.1$. For a log-normal distribution we have

$$E[X] = e^{\mu + \frac{1}{2}\sigma^2}$$

Hence if we put $\mu = -\frac{1}{2}\sigma^2$, we get $E[X] = 1$. If an agent would improve his or hers position considerably by winning the auction, he or she should be inclined to place a higher bid. To take this into account in our model, we have used

$$\mu = \ln\left(0.7 + 0.3(1 - \frac{\text{utility of current state}}{\text{utility of new state}})\right) - \frac{1}{2}\sigma^2$$

The bidder then places a bid

$$\text{bid} = X \cdot \left(0.2 + 0.8 \max\left[\frac{N-1}{N}, \frac{1}{2}\right]\right) \cdot \text{quoted price.}$$

The bidder with the highest bid wins the auction. Since the last two factors are the same for all agents, only the value of X determines the winner. The two other factors are, however, important in the comparison of reservation prices and in the updating of housing prices in the towns. When is a sale completed? The seller inspects the winning bid, and if this bids exceeds his or hers reservation price, the sale is carried out. If not, the house remains in the pool of houses for sale. The reservation price is computed from formulas similar to the formulas we used in the utility considerations above.

As a technical note, degenerate cases sometimes occur in the formulas above, and the program takes such cases into account. Moreover we have capped bids when they are 7.5% lower/higher than the quoted prices. Capping the bids in this way, we avoid wild behavior occurring when quoted prices are based on a small number of transactions, in extreme cases only one.

3.5.2 Housing supply

The initial supply of housing is determined by a regional government planning entity, and new houses are in general built according to a minimum frequency of 5% yearly in each town. In addition, if a town experiences a high demand and a correspondingly high increase in housing prices in the previous year, then this is allowed to be reflected in a high building frequencies of new houses, provided by either public or private agents.

$$HS_j^t = \begin{cases} HS_j^{t-1} \cdot 1.05 \cdot \left(\frac{P_{hj}^{t-1}}{P_{hj}^{t-2}}\right)^{\gamma} & \text{if} \quad \frac{P_{hj}^{t-1}}{P_{hj}^{t-2}} > 1.05 \\ 1.05 & \text{otherwise} \end{cases}$$

where HS_j^t is the housing supply in town j in year t, and P_{hj}^t is the housing price per squared meter in town j in year t. γ is the elasticity of housing supply with respect to the price increase observed in the previous year.

4 Defining the initial state and a benchmark for experiments

The agent-based modelling framework is used to generate commuting matrices, corresponding to different specifications of the spatial structure. We are monitoring how different scenarios and numerical experiments affect the estimates of the distance deterrence parameter from the standard doubly-constrained gravity model. This is analogous to comparative static approaches in a pure analytical framework, focusing on the impact of partial changes in an exogenous variable on a set of endogenous variables. However, our modeling framework is dynamic. Agents make decisions based on life cycle considerations, and the state of the system changes continuously as a response to numerous independent individual decisions. The analysis is based on a set of simplifying assumptions, we have for instance abstracted from worker and job heterogeneity. Still, the curves in the figures to follow reflect the outcome of very complex mechanisms, like the competition for jobs and houses, for households which tend to have more than one worker.

As a first step, we start with a population of 15000 17-year old. Initially, the individuals are evenly distributed across the towns in our geography, with the exception of the cbd (zone E), which is allocated 5 times more people than the other towns. The same applies to the initial number of 4000 houses. Through rules defined by Norwegian average rates of marrying, births, deaths, etc., the members of this population then interact over 300 years, which is by a good margin sufficient to generate a population very similar to the Norwegian in a demographic sense. After these 300 years of initialization, housing and labour market characteristics are introduced, as important input for location decisions of households and firms.

The system was then run for another 50 initializing years, where agents account for relevant characteristics of the housing and labour market, like housing prices, traveling costs, and wages. This dynamic system, with a continuously changing population, does not reach a steady state equilibrium. Still, we have done experiments on the level of migration and commuting costs, the balance between jobs and workers, and a set of parameters, to reach a state after 50 years with reasonable values of endogenous variables, like housing prices, unemployment rates and wages. The mechanisms and parameter values of our benchmark scenario are as follows:

Preferences. The weight attached to general consumption, α_i in Equation 4, is allowed to vary randomly, uniformly distributed across individuals, within the interval (0.3-0.7).

Housing supply. The housing supply elasticity $\gamma = 1$, see Section 3.5.2. The initial price of building a house is 5000 per square meter, and the housing price construction price increases by 1% per year. It takes 1 year to construct a house.

The spatial distribution of local and basic sector jobs. The local sector employment in the region is assumed to be 20% of total population in the region, distributed between towns according to the same parameterization as in McArthur et al. (2014, 2020). In addition, we do consider a case where the relevant spatial distribution of local sector employment is substituted by an assumption of equal local sector density in all the towns, equal to 20% of the local population. The spatial distribution of basic sector employment is presented in Table 1. No attempts have been made to explain the distribution by spatial differences in innovativeness, creativity, knowledge, entrepreneurship, etc.

Wages The wage in year 0 is NOK 100000 in all the zones except the cbd, zone E, where the yearly wage rate initially is assumed to be NOK 115000. The unemployment insurance is set to be NOK 60000 in all the zones in year 0. Both wages and the unemployment insurance are assumed to increase by 2.5% yearly. The parameter representing the sensitivity of wages to changes in the local level of unemployment is given by $\lambda = 0.1$. In addition, there is a 28% income tax, while mortgages and life-time incomes are calculated by the use of a discount rate of 2.5%.

Commuting costs The generalized round-trip commuting costs are assumed to be NOK 0.6 per kilometer in year 0, incurred over 200 working days per year. The commuting costs are increasing by 2.5% per year.

The chosen size of the initial population and jobs reflect a trade-off between computing time and the call for for unveiling robust relationships between different variables. Let $BASE_j^t$ be the number of basic sector jobs in town j in year t, POP_j^t is the population in town j in year t, while TOT_j^t is the total number jobs in town j in year t. Table 1 offers information of how the population and the jobs are distributed across the towns after 50 years, given the initial distribution of basic sector jobs. The table in addition offers information on the unemployment rates (U_j), the housing prices (P_{hj}, and the wages (w_j) in the 12 towns in year 50. Notice in particular that the cbd, town E, has many times higher housing prices than the other towns. This corresponds to a high concentration of jobs, covered by a substantial in-commuting from the other towns in the system. Notice also that the high demand for labour in the cbd has caused an increased nominal wage disparity between the cbd and the other towns, while the relative difference has remained at the approximately same level over time.

Table 1: Zonal values of basic variables in the benchmark scenario

zone	$BASE_j^0$	POP_j^{50}	TOT_j^{50}	U_j^{50}	P_{hj}^{50}	w_j^{50}
A	430	2 049	830	8.1%	23 863	329 940
B	270	1 750	603	7.9%	24 354	318 676
C	220	1 604	507	8.8%	24 332	321 420
D	60	1 894	420	9.7%	22 985	309 731
E	2 200	3 139	4 491	9.3%	101 361	369 140
F	350	1 545	472	10,0%	24 817	314 013
G	310	1 857	575	10,8%	25 048	310 418
H	460	1 703	594	10.4%	24 853	314 425
I	100	1 288	284	10.1%	24 743	302 884
J	330	1 623	598	10.8%	23 467	305 140
K	350	1 683	628	9.3%	23 480	307 777
L	60	1 431	264	10.3%	23 811	320 838
Region	5 140	21 566	9 679			

5 Results of changing the spatial structure

Fotheringham (1981) and Lo (1991) define spatial structure as "the size and configuration of origins and destinations"of a regional system, while Tiefelsdorf (2003) emphasizes "the mutual distances among representative points of the region". Based on such definitions, any changes in the road transportation infrastructure that are altering the positions of the different towns are considered as changes in spatial structure, as are changes in the spatial distribution of jobs.

Our approach is to introduce specific changes, like the location of the regional center, the distribution of basic sector jobs throughout the zones, the road transportation network and the compactness of the system, represented by the distances between the zones. We do controlled experiments, by considering one exogenous change at a time. For each change, we run our agent-based model. This model simultaneously predicts how the change affects

the housing market in terms of housing prices and the provision of new houses

the labour market in terms of wages and the spatial distribution of local sector jobs

The new spatial equilibrium location pattern results from how changes in spatial structure and accessibility patterns affect the local housing demand and shopping location decisions. Shopping is represented by the local sector density function explained in Section 3.4, while the effects on local housing demand is explained by the core element of the bid rent theory. The effects of changes in the residential location pattern and in shopping destinations are expanded by economic base mechanisms, inducing a new spatial distribution of jobs and people. The agent-based modeling framework is integrating land use and transportation. Hence, the predicted change in the location pattern is mirrored by corresponding changes in the activity-based commuting flows. This means that the agent-based model generates a new "observation"of a commuting matrix, evolving from any exogenous shock that is introduced. All the "observed"changes in the location pattern and the commuting flows are next imputed into the doubly-constrained gravity model, as a framework for estimating new values of the distance deterrence parameter β in Equation 1. Since the underlying preferences are kept constant, any change in parameter estimates reflects the specific characteristics of the spatial structure. The cases that will be studied differ from our benchmark scenario as follows:

Case CBD The cbd of the region is town B rather than town E. As compared to our benchmark situation, all zone-specific information is swapped between these two zones. This applies for instance to the number of basic sector jobs.

Case EVEN The distribution of basic sector jobs are more evenly spread throughout the zones than in our benchmark scenario, Hence, this test defines a less centralized system.

Case BRIDGE We introduce a major change in the road transportation network, in that a bridge/tunnel is connecting the towns B and E.

Case LSD The local sector density is 0.2 in all towns, rather than the spatial distribution of local sector densities as suggested by Gjestland et al. (2006), see Section 3.4.

Case DISPERSION For a system of towns that is more compact than the benchmark scenario, we let all the distances in the system be reduced by a factor of 0.5, while all the distances are increased by a factor of 1.5 in a more dispersed configuration of towns.

It is reasonable to think of the cases EVEN and BRIDGE to materialize at a specific point in time. The position of a town as the regional centre on the other hand, can be argued to develop as a result of a more slow-moving process. Rather than introducing a change of cbd in year 50, we therefore compare our benchmark scenario to an alternative where the cbd is assumed to be town B from the start. Similarly, it also makes more sense to discuss both the cases LSD and DISPERSION in developing from year 0, rather than appearing at a specific point in time.

5.1 An altenative location of the cbd; case CBD

The result of case CBD on $\hat{\beta}$ is illustrated in Figure 2. The initializing period reflects location responses to the job and residential opportunities. Eventually, the location pattern approaches a state where the spatial distribution of jobs and households is relatively stable across the 12 towns. Still, in this dynamic system, with births, deaths, marriages, relocations, etc., the location pattern and the estimated distance deterrence parameter do not converge in the sense that a specific value is reached. The system rather approaches a state where the corresponding estimates of the distance deterrence parameter is centering around a specific level.

It further follows from Figure 2 that the values of the distance deterrence parameter is systematically lower in the case where town B is the regional centre. Before explaining this difference in observed commuting response to distance, notice that the change of cbd has a considerable impact on variables that are related to commuting. It is of course intuitively reasonable that the change of cbd-location benefits the least populous area, which in year 50 has 42,9% of the jobs and 42,2% of the population in the region. In the benchmark scenario, the corresponding figures were 24,2% and 35%, respectively.

The position as the cbd reflects a high concentration of local sector jobs, which comes in addition to the higher concentration of basic sector jobs that is allocated to the cbd. In the case where the cbd is located at the least populous area, this concentration of jobs attracts more long-distance commuting. Consequently, the observed commuting matrix has more commuting between distant O-D combinations, as an explanation of the markedly lower value of the distance deterrence parameter that is illustrated in Figure 2. As a general conclusion, this suggests that if many people live in a long distance from the cbd, then there will be a tendency that the observed commuting flow data results in a low estimated distance deterrence.

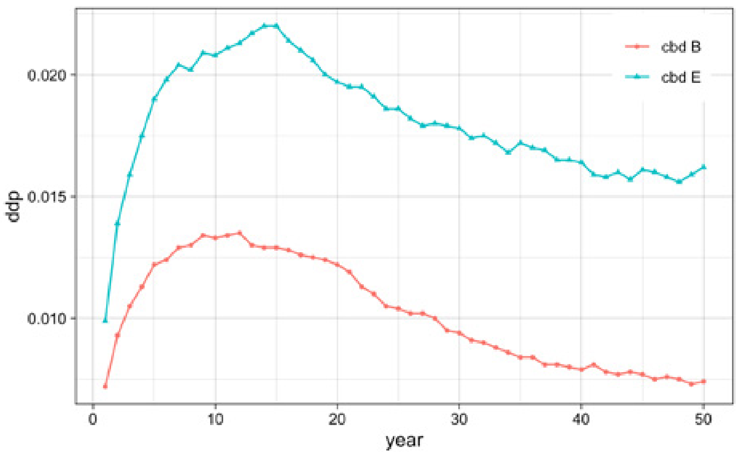


Figure 2: Estimates of the distance deterrence parameter over the first 50 years, for two alternative locations of the cbd in the region.

5.2 A spatially more even distribution of basic sector jobs; case EVEN

Figure 3 gives an illustration of $\hat{\beta}$ in the cases EVEN and BRIDGE. The figure is defined up to year 65, to account for possible systematic trends that may be present even after 50 years of initialization and adaption to the initial specification of exogenous variables and parameters.

In case EVEN, 1100 basic sector jobs are redistributed from the cbd, and each of the 11 other towns are allocated 100 new basic sector jobs. It follows from Figure 3 that this results in a commuting pattern corresponding to a higher $\hat{\beta}$ than in our benchmark scenario. Notice also from Figure 3, the tendency that the difference ($\hat{\beta}^{\text{EVEN}} - \hat{\beta}^{\text{benchmark}}$) is increasing over time, peaking around year 61.

It takes quite a long time after the job redistribution shock, before a commuting pattern emerges that is corresponding to a relatively stable value of β. This value is higher than in the benchmark case, reflecting a commuting pattern where distance appears to be more of a barrier. The commuting towards the cbd is, naturally, substantially reduced when jobs are decentralized. In case EVEN, around 24% of the workers living outside the cbd commute towards the cbd in year 65, while this applies for around 36% of the workers in the benchmark case. With reduced prospects of receiving job offers in the cbd, workers will to a larger degree settle down with solutions involving low commuting expenses. A household may for instance be content with a

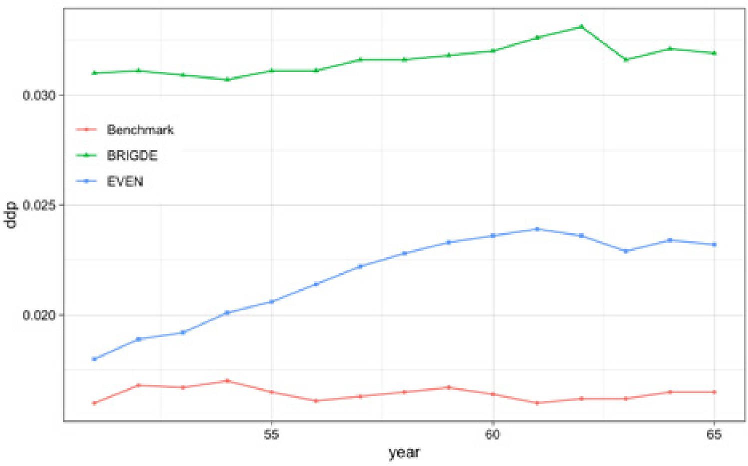


Figure 3: Estimates of the distance deterrence parameter in cases with a more even spatial distribution of basic sector jobs, and a bridge connecting town E (the cbd) and town B.

solution where both spouses work in the town where they live.

In this dynamic system, such a search for solutions involving low commuting expenses may progress over long time before it converges towards a dynamic equilibrium level. Consider the proportion of workers who work in the same town where they live. For case EVEN, this proportion was around 24% in year 65, for workers living outside the cbd, while the corresponding proportion was around 18% in the benchmark scenario. This contributes to explain the higher $\hat{\beta}$ in case EVEN, with workers who are seemingly more reluctant towards long-distant commuting.

5.3 A new bridge between towns B and E; case BRIGDE

A bridge between the towns B and E also defines a new spatial configuration of towns. As illustrated in Figure 3, the new bridge is causing a marked and persistence increase in the yearly estimates of the distance deterrence parameter. This impact on $\hat{\beta}$ comes as an immediate response to the bridge. At this point in time, the commuting pattern represents an adaptation to the situation without a bridge. Hence, many O-D combinations in a relatively short distance to each other, on either side of the barrier, have very few commuters. Workers then appear to be quite reluctant to commute over such distances, evaluated by the new distance matrix.

The adaptation to the new situation goes on over a long period, with workers searching for O-D combinations making them well off, in terms of wage, housing price, and commuting expenses. In year 65, the commuting between the two areas on either side of the topographical barrier (bridge) has increased by around 11% compared to the situation in year 50. This increase is entirely explained by the commuting from the smallest area towards the cbd-area. As a result of the bridge, high-wage jobs in the cbd have become more appealing for workers living across the former barrier. Over time, there is a tendency that they replace the workers from the most distant towns of the cbd-area from working in the cbd. The system then works in the direction of a new dynamic equilibrium with less long-distant commuting than prior to the changed road network. This contributes to explain the persistently higher estimate of the distance deterrence parameter than in the benchmark scenario, with workers seemingly more reluctant towards long-distance commuting than prior to the investments in road transportation infrastructure.

5.4 A less clustered distribution of local sector jobs; case LSD

In case LSD, local sector employment in the cbd is considerably downsized, and less commuting is attracted towards the regional centre. This case ignores the possibility of economies of scale and scope in shopping, that is ignoring the basic mechanisms underlying Reilly's law (Reilly 1931). The corresponding shopping behaviour deviates substantially from the more centralized pattern in the benchmark scenario. The effect on $\hat{\beta}$ is illustrated in Figure 4.

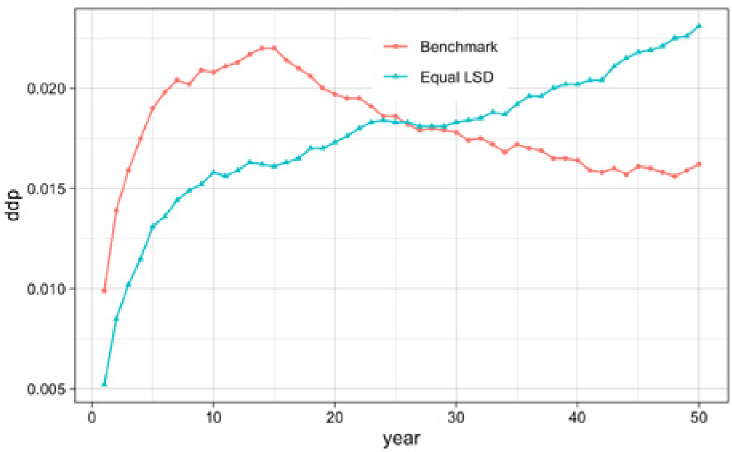


Figure 4: Estimates of the distance deterrence parameter in the case where local sector densities are proportional to the size of the population.

Case LSD is based on the assumption that alternative shopping behaviour has been unchanged since the beginning of the period under consideration, rather than as a sudden change at a specific point in time. It appears from Figure 4 that $\hat{\beta}$s continue to increase even after the initializing period needed for the benchmark scenario to reach a state with relatively stable $\hat{\beta}$s.

Despite the different time perspectives in the experiments, the development in case LSD is more similar to case EVEN, where the period of increasing $\hat{\beta}$s lasts considerably longer than for the two other cases in Figure 3. Both case EVEN and case LSD correspond to a more even spatial distribution of jobs across the towns in the geography. Hence, there will be less commuting towards the cbd, and the prospects of getting better paid jobs are reduced. Still, workers continue to search for solutions involving low commuting expenses, high wages and low housing prices for the household. This is a slow process in this dynamic system, and it can be useful to study for instance what happens to the relative number of workers taking the advantage of working and living in the same town. The development of the percentage number of non-commuters is illustrated in Figure 5.

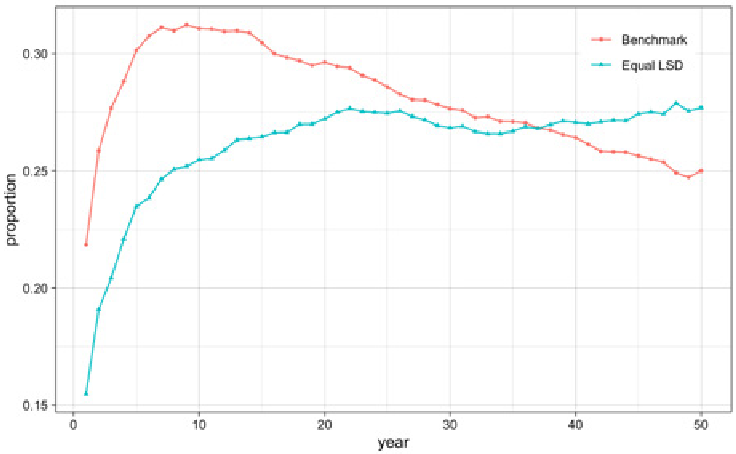


Figure 5: The percentage number of workers living and working in the same town, in the benchmark scenario and in case LSD.

Notice that the pattern of the two lines in Figure 5 has some resemblance with the lines in Figure 4. It makes sense that a high number of non-commuters corresponds to a high value of $\hat{\beta}$. It also makes sense that the number of non-commuters eventually falls in our benchmark scenario, but remains stable in case LSD. In the benchmark scenario, more workers succeed in taking advantage of a high-wage employment in the cbd. Figure 5 reflects a pattern in the benchmark scenario where many workers first go for a solution with work and residence in the cbd. Over time, however, workers living in other zones tend to search for the high-wage jobs in the cbd, choosing a situation with commuting rather than moving into the cbd, where housing prices are higher than elsewhere in the geography. This leads to a situation where in-commuters occupy jobs in the cbd, contributing to explain the tendency of a falling number of non-commuters. This is to a smaller degree the case when local sector jobs are more evenly spread throughout the geography, reducing the prospects of getting highly paid jobs in the cbd.

Hence, the explanation of the relatively high $\hat{\beta}$s in case LSD is the same as for case EVEN. In cases with a less centralized pattern of jobs, the relevant parameter estimates tend to be higher, no matter if it is caused by a decentralization of local or basic sector jobs.

5.5 Different degrees of spatial dispersion between towns; case DISPERSION

The estimates of β represented by the curve denoted "Compact"in Figure 6 refer to a case where all distances are reduced by half, while the curve "Dispersed"is based on an experiment where all distances between the towns are increased by a factor of 1.5.

The most compact system of towns results in substantially higher $\hat{\beta}$s. A highly paid job in the cbd is attractive, even if it calls for commuting from the towns which are most distant to the cbd in this compact system. This pulls in the direction of a low value of β. Aside from working for a high wage in the cbd, it is still attractive, even in this compact system, to work and live in the same town, saving the household for commuting expenses. With many non-commuters in a system with short distances, workers appear to be highly distant-deterrent in commuting. The preference towards non-commuting pulls the $\hat{\beta}$s in the opposite direction of the centripetal forces originating from the high wage in the cbd. According to the "Compact"curve in Figure 6, this second force is more dominating in a compact system than in the benchmark scenario. The situation is the reverse for the more dispersed spatial configuration of towns. Even in this case, with long distances between the towns, some workers choose to commute and benefit from the high wage in the cbd, and the observed pattern corresponds to a hypothesis that workers are not strongly deterred by distance in their choice of an O-D combination.

The curves in Figure 6 were interpreted to result from balancing the worker's wish for a high wage and the benefit of avoiding commuting expenses. As a reasonable presumption, commuting

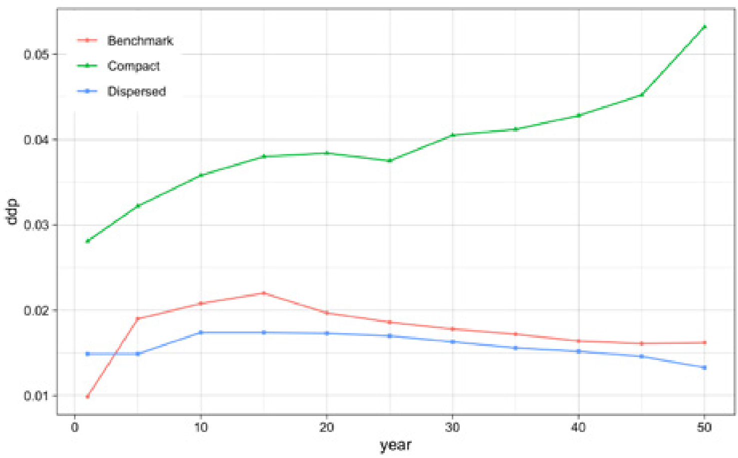
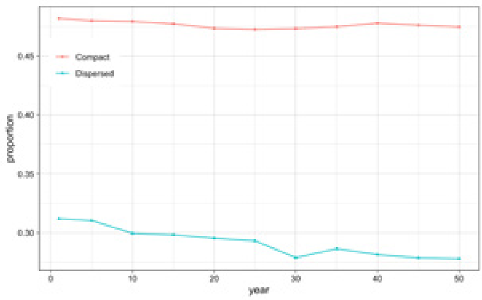


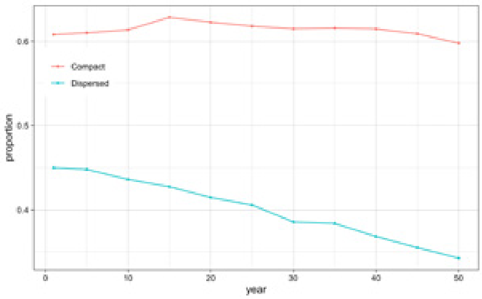
Figure 6: Estimates of the distance deterrence parameter in cases with different degrees of spatial dispersion in the pattern of towns in the geography.

will be higher in the compact system than in a system where the towns are more spread-out in the geography. This a priori expectation is supported in Figure 7a. A considerably higher number of workers are commuting towards the cbd in the compact system. In a case where the other towns are closer to the cbd, it follows from the LSD function in our model that their households will do more of their shopping in the cbd. Due to economies of scale and scope in shopping, local sector jobs will then be more clustered in the cbd. This additional centripetal force contributes to explain the high number of in-commuters to the cbd in this system.

The clustering of local sector activities promotes commuting. However, as is evident from Figure 6, this does not result in low $\hat{\beta}$s. The increased commuting towards the cbd is more than counteracted by the tendency to live and work in the same town. The compact system has a very polarized commuting pattern, with a strong tendency that the workers either commute towards the cbd, or do not commute at all. There are not much commuting between O-D combinations which are not involving the cbd. This is more common in the more dispersed system, where a substantially higher number of local sector jobs are located outside the cbd. As illustrated in Figure 7b, the compact system has a substantially higher proportion of non-commuters than the more dispersed spatial pattern of towns. This reflects a tendency that the relatively few local sector jobs that are left outside the cbd tends to be occupied by local workers. Despite their high commuting into the cbd, the workers in the compact system then apparently are more deterred by distance in their spatial labour market interaction. The percentage increase in commuting is lower than the 50% reduction in distances.



a) In-commuters to the cbd



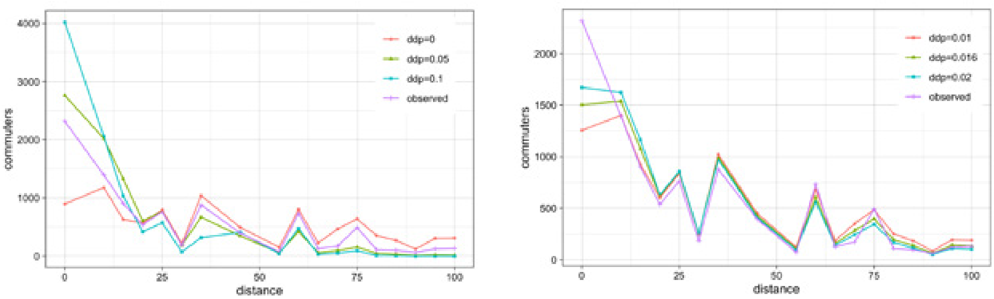
b) Non-commuters

Figure 7: The proportion of workers who are working but not living in the cbd, and the proportion of workers who are living and working in the same town. A compact system of towns is compared to a more dispersed system, with longer distances between the towns.

The relocation of local sector jobs causes a more imbalanced spatial system of jobs and housing. The variation in the job/housing ratio in an area iinfluences commuting, and this ratio is in general emphasized in the literature (see for example Sultana (2002), Schwanen et al. (2004), Lin et al. (2015), Kim and Choi (2019), Guo et al. (2019), and Moos et al. (2018)). This kind of imbalance explains the tendency of increased commuting into the cbd that is illustrated in Figure 7a. In this case, however, the imbalance is due to a relocation of jobs to a centrally located town in a compact system. This does not induce a lot of long-distance commuting, which would pull in the direction of a low $\hat{\beta}$.

6 Model performance and parameter sensitivity of making predictions.

In this section, we provide information on model performance, and discuss how sensitive the predicted commuting flows are to the value of $\hat{\beta}$ in the standard doubly-constrained gravity model. Figure 8 offers information on the predicted number of workers commuting specific distances, for different values of β. In part a) of the figure, the values of β are deviating substantially from the entropy-maximizing value of $\hat{\beta} \approx 0.016$. In part b) of the figure, the values are in a lot closer range to $\hat{\beta} \approx 0.016$. Notice that the scaling for the vertical axis is different in the two parts of the figure. Taking this into account, it is obvious from the figure that the values of β in the range close to 0.016 give a substantially better fit to the observations than the more extreme values in part a) of the figure.



a) Extreme values of β b) β's close to the entropy-maximizing value

Figure 8: Commuting flows from our benchmark agent-based scenario are compared to predicted commuting flows for different values of the distance deterrence parameter in the doubly-constrained gravity model.

The prediction errors in Figure 8a) are according to an expected pattern. Very high values of β, correspond to a situation where the workers resist to commuting over long distances. Hence, it makes sense that the gravity model is overpredicting the number of non-commuters, and is underpredicting the commuting over long distances in the case where $\beta = 0.1$. This tendency is less pronounced for $\beta = 0.05$, while a value of $\beta = 0$ reflects a situation where the workers tend to be happy to be employed anywhere, without considering distance as a barrier.

Part b of Figure 8 illustrates that the predicted commuting flows are not very sensitive to small deviations from the entropy-maximizing value of β, but that there is still room for significant predictions errors. The prediction errors are in particular discernible for intraurban commuting, indicating that the standard doubly-constrained gravity model does not adequately account for the propensity that workers live and work in the same town.

Table 2 offers more accurate information on the model performance, for different values of β. For this purpose, we use the standardized root mean square errors (SRMSE), that was recommended by Knudsen and Fotheringham (1986) as an accurate measure for the performance of a model to replicate a data set of a spatial system. The predicted commuting patterns are compared to the commuting pattern that is following form running the benchmark scenario for 65 years. It follows from Table 2 that the values of the SRMSE are apparently not very sensitive to deviations from the entropy-maximizing value of β. Still, we know from Figure 8 that $\beta = 0.05$ gives a considerably poorer fit than values of β close to 0.016. Hence, an increase in SRMSE from 0.42 to 0.46 represents a substantially poorer fit to data, and a value of SRMSE close to 1, or even around 0.6, corresponds to a predicted commuting pattern that is fundamentally different from the observed pattern.

Table 2: The SRMSE of the standard doubly constrained gravity model for different values of β. The observed O-D matrix is given by the benchmark scenario, year 65.

zone	$\beta = 0$	$\beta = 0.01$	$\beta = 0.016$	$\beta = 0.02$	$\beta = 0.05$	$\beta = 0.1$
SRMSE	0.624	0.454	0.417	0.426	0.463	1.062

The gravity model can for example be used to predict the impact on commuting flows if basic sector jobs are more evenly distributed across the geography, or if a new bridge is connecting different areas. As demonstrated above, however, one major problem is that the distance deterrence parameter is not autonomous to such changes. If we use the value of β that was estimated from the ex ante situation, then this will lead to a severely wrong prediction of the impact on commuting flows. An appropriate model for making predictions should account for relevant characteristics of for example the spatial structure. However, entering into a discussion of model extensions is beyond the scope of this paper.

As pointed out in for example Wilson (2010), a reduction in total commuting expenditures is equivalent to an increased value of the β parameter. This is reflected in Figure 8. High values of β correspond to a high number of non-commuters, and not much commuting over long distances, while low values of β results in higher aggregate commuting expenditures.

The value of β is related to the concept of commuting tolerance, that is frequently used and discussed in the literature (see for example Clark et al. (2013), who indicate a tolerance level in between 30 and 45 minutes). It is not straightforward to identify such a tolerance level for the system treated above. The system has a relatively low number of agents, with an irregular distribution of possible commuting distances. This irregularity partly reflects the topographical barrier, that separates the geography into two areas. An unbalanced jobs/housing ratio between the two areas contributes to explain the demand for some long-distance commuting, over for example 75 km. Hence, a smoothly falling curve cannot be expected. Still, Figure 8 at least demonstrates that such a tolerance level will be negatively related to the value of β.

The experiments that are run in this paper all tend to report lower values of $\hat{\beta}$ than are usually reported in empirical studies of commuting flows. Based on commuting data from Norwegian regions, and an exponential representation of distance in the model, Gitlesen and Thorsen (1998, 2000), and McArthur et al. (2011, 2013), estimate values of β around 0.07. The experiments have demonstrated that there are many possible explanations for the divergence between the benchmark agent-based commuting pattern, and real world observations. If the real world has

- a more compact spatial structure, with short distance between the central places
- no barriers in the transportation network
- a less centralized distribution of basic and local sector jobs,

we have seen that all these factors will pull in the direction of a commuting pattern corresponding to a higher value of the distance deterrence parameter.

7 Concluding remarks

The agent-based experiments generated a population that in a demographic sense is very similar to the Norwegian. We primarily used this experimental design as a consistent approach to discuss the interpretation of the distance deterrence parameter in a spatial interaction model, and the stability of parameter estimates over different controlled experiments. The main contribution is to demonstrate how these parameter estimates reflect spatial structure characteristics.

Table 3 summarizes some aspects of the results. The estimates of β refer to the last year of the respective experiments. Some of the experiments have been running for 50 years after the initialization, while others have been running for 15 years after a shock was introduced in year 50. There is of course a risk that in particular the values of β taken from the latter experiments are still trending towards a new dynamic equilibrium level. It still follows from Table 3 that the parameter estimates vary considerably across the different experiments. The estimated effect of variations in distance is in particular sensitive to the compactness of the configuration of central places, but they also respond significantly to changes in the transportation infrastructure and the centralization of local and basic sector jobs. To summarize, commuting is estimated to be a lot more deterred by distance in a compact system, with short distances between central places, with no barriers in the transportation network, and a decentralized distribution of jobs.

Table 3: Parameter estimates, model performance, and the coefficient of variation (CV) of the jobs/housing (J/H) balance between the towns in different experiments.

	$\hat{\beta}$	SRMSE	J/H balance, CV
Benchmark	0.0162	0.4250	0.3270
Case CBD	0.0102	0.5434	0.3896
Case EVEN	0.0232	0.4829	0.2709
Case BRIDGE	0.0319	0.3263	0.3199
Case LSD	0.0231	0.4570	0.2620
Case COMPACT	0.0532	0.9557	0.5983
Case DISPERSED	0.0133	0.4810	0.3186

Hence, our experiments demonstrate that $\hat{\beta}$ from a standard gravity model vary substantially with respect to the data-generating design. This raises an interpretational concern; $\hat{\beta}$ from the standard gravity model is not an unbiased estimate of how variations in distance affect commuting. Another concern is related to the predictability. Assume that the transportation network is changed, by building a new bridge connecting the two areas that are separated by a topographical barrier. What parameter value should be used in predicting the induced commuting from a standard gravity model? As pointed out in Section 6, one problem is that the parameter is not autonomous to the change in the transportation network. Basically, however, the problem is that the standard doubly-constrained gravity model is not an adequate representation of the geography. Our experiments have demonstrated that the model specification should explicitly account for spatial structure characteristics. By integrating such variables adequately, the resulting modeling device will potentially be more suitable in making reliable predictions.

Table 3 also provides information of the model performance (SRMSE). The standard doubly-constrained gravity model in particular fails to replicate commuting flows in a compact system, with short distances between the towns. Keep in mind, however, that this experiment has relatively large spatial wage disparities, with around 15% higher wages in the cbd. This is maybe not a likely scenario in such a compact system, but it nevertheless sorts out a possible scenario where the standard gravity model does not at all perform well to explain commuting flows. In such a case, the model strongly underpredicts the commuting flows into the cbd.

Finally, Table 3 offers information on spatial disparities in the Job/Housing (J/H) balance. A high value of the coefficient of variation (CV) reflects an unbalanced J/H distribution across the towns. It is well known in the literature that the commuting pattern depends on the local balance of employment and housing, and that this leaves a potential for spatial planning policies to move the local economy into a more sustainable direction (see for example Schwanen et al. (2004), Lin et al. (2015), Kim and Choi (2019), Guo et al. (2019), and Moos et al. (2018)). This discussion is beyond the scope of this paper, but notice at least from Table 3 that the case where town B is the cbd results in unbalanced systems, while case EVEN and case LSD are more balanced systems. In comparing these cases, the hypothesis is supported that unbalanced systems results in a lot of commuting and lower values of $\hat{\beta}$ than more balanced systems.

The evidence in Table 3 is not unambiguous, however. The compact system results in a very high clustering of local sector jobs towards the cbd. Hence, the system is strongly unbalanced in terms of J/H. The system has a high level of commuting, but the dominating part of this commuting involves the cbd, which is centrally located. Hence, the gravity model estimates a high $\hat{\beta}$, serving as an example that an unbalanced system does not necessarily lead to a low $\hat{\beta}$.

Summarized, we think that the experiments presented in this paper have demonstrated that different characteristics of the spatial structure should be explicitly accounted for to obtain reliable, unbiased, estimates of β in spatial labour market interaction. The results provide a useful guideline for evaluating results in empirical studies. This applies for instance for interregional comparisons of commuting behaviour, and for procedures related to the prediction of induced commuting and willingness-to-pay for investments in transportation infrastructure.

References

[1] Alonso, W, 1964, "Location and land use: towards a general theory of land rent; Harvard University Press: Oxford University Press, London.

[2] Anas, A, 1983, "Discrete choice theory, information theory and the multinomial logit and gravity models",*Transportation Research B*, 17, pp. 13-23.

[3] Anas, A, 1984, "Discrete Choice Theory and the General Equilibrium of Employment, Housing, and Travel Networks in a Lowry-Type Model of an Urban Economy", *Environment and Planning A*, 16, 1489-1502.

[4] Batty, M, 2005, Cities and complexity: understanding cities through cellular automata, agent-based models and fractals, the MIT Press

[5] Cliff A D, R L Martin, J K Ord, 1974, “Evaluating the friction of distance parameter in gravity models”, *Regional Studies*, 8, 281-286

[6] Curry, L, D A Griffith, E S Sheppard, 1975, “Those gravity parameters again”, *Regional Studies*, 9, 289-296.

[7] Desta, E and B W M Pigozzi, 1991, “Further experiments with spatial structure measures in gravity models”, *Tijdschrift voor Economische en Sociale Geografie*, 82, 3, 220-226.

[8] Duranton, G and D Puga, 2004, “Micro-foundations of urban agglomeration economics”, in Henderson J V and J F Thisse, Handbook of regional and urban economics 4.

[9] Erlander, S and N F Stewart, 1990, “The Gravity Model in Transportation Analysis — Theory and Extensions”, VSP, Utrecht.

[10] Fotheringham A S, 1981, “Spatial structure and distance-decay parameters”, *Annals of the Association of American Geographers*, 71, 425-436.

[11] Fotheringham A S, 1983a, “Some theoretical aspects of destination choice and the relevance to production-constrained gravity models”, *Environment and Planning A*, 15, 1121-1132

[12] Fotheringham A S, 1983b, “A new set of spatial interaction models: the theory of competing destinations”, *Environment and Planning A*, 15,15-36.

[13] Fotheringham A S, 1986, “Modelling hierarchical destination choice”, *Environment and Planning A*, 18, 401-418.

[14] Fotheringham A S, M J Webber, 1980, “Spatial structure and the parameters of spatial interaction models”, *Geographical Analysis*, 13, 33-46.

[15] Gitlesen J P and I Thorsen, 1998, “Empirical Evaluation of Alternative Model Specifications to Predict Commuting Flows”, *Journal of Regional Science*, 38, 2, 273-292.

[16] Gitlesen J P and I Thorsen, 2000, “A Competing Destinations Approach to Modeling Commuting Flows: A Theoretical Interpretation and An Empirical Application of the Model”, Environment and Planning A,

[17] Guo, J, T Feng and H J P Timmermans, 2020, "Co-dependent workplace, residence and commuting mode choice: Results of a multi-dimensional mixed logit model with panel effects", *Cities*, Volume 96,

[18] Irwin, E G, "New directions for urban economic models of land use change: incorporating spatial dynamics and heterogeneity", *Journal of Regional Science*, 50(1), 65-91.

[19] Ishikawa, Y, 1987, "An empirical study of the competing destinations model using Japanese interaction data", *Environment and Planning A*, 19,1359-1373.

[20] Kim, Chunil and C Choi, 2019, "Towards sustainable urban spatial structure: Does decentralization reduce commuting times?", *Sustainability*, 11, 182,

[21] Knudsen, C D, and A S Fotheringham, 1986, "Matrix comparison, goodness-of-fit and spatial interaction modeling", International Regional Science Review", 10, 127-147.

[22] Krishna, V, 2002, *Auction Theory*, San Diego, USA: Academic Press

[23] Lin, D, A Allan, and J Cui, 2015, "The impact of polycentric urban development on commuting behavior in urban China: Evidence from four sub-centers of Beijing", *Habitat International*, 50, 195-205.

[24] Lo L, 1991, "Spatial structure and spatial interaction: a simulation approach", *Environment and Planning A*, 23, 1279-1300

[25] Lo L, 1992, "Destination interdependence and the competing destinations model", *Environment and Planning A*, 24,1191-1204.

[26] McArthur, D P, I Thorsen and J Ubøe, 2010,"A Micro-Simulation Approach to Modelling Spatial Unemployment Disparities ", *Growth and Change*, 41, 3, 374-402

[27] McArthur, D P, I Thorsen and J Ubøe, 2012,"Labour market effects in assessing the costs and benefits of road pricing ", *Transportation Research Part A: Policy and Practice*, 46, 2, 310-321

[28] McArthur, D P, I Thorsen and J Ubøe, 2014, "Employment, transport infrastructure and rural depopulation: a new spatial equilibrium model ", *Environment and Planning A*, 46 (7), 1652-1665.

[29] McArthur, D P, I Thorsen and J Ubøe, 2020, "Some consequences of ignoring relocations in the cost-benefit analysis of transportation infrastructure investments", in Thill, J-C, Innovations in urban and regional systems: contributions from GIS&T, Spatial analysis and location modeling, Springer, 137-164.

[30] McArthur, D P, G Kleppe, I Thorsen and J Ubøe, 2011, "The spatial transferability of parameters in a gravity model of commuting flows", *Journal of Transport Geography*, 19, 4, 596-605.

[31] McArthur D P, G Kleppe, I Thorsen and J Ubøe, 2013, "The impact of monetary costs on commuting flows", *Papers in Regional Science*, 92, 1, 69-86.

[32] Moos, M, N Revington, and T Wilkin, 2018, "Is there suitable housing near work? The impact of housing suitability on commute distances in Montreal, Toronto, and Vancouver", *Journal of Urbanism*, Volume 11, 4,

[33] Muth, R F, 1969, "Cities and housing: the spatial pattern of urban residential land use ", Chicago and Londin: The University of Chicago Press.

[34] Nævdal, G, I Thorsen and J Ubøe, 2002, "A Network Approach to Commuting", *Journal of Regional Science*, 39,1, 73-101

[35] Page, S E, 1999, "On the emergence of cities", *Journal of Urban Economics*, 45,1, 184-208.

[36] Pellegrini P A, A S Fotheringham, (2002, "Modelling spatial choice: a review and synthesis in a migration context", *Progress in Human Geography*, 26, 487-510.

[37] Persyn, D and W Torfs, 2016, "A gravity equation for commuting with an application to estimating regional border effects in Belgium", *Journal of Economic Geography*, 16, pp. 155-175.

[38] Reilly, WJ, 1931, The Law of Retail Gravitation, New York: G. P. Putman and Sons.

[39] Schwanen, T, F Dieleman, and M Dijst, 2004, "The impact of metropolitan structure on commuting behavior in the Netherlands: a multilevel approach", *Growth and Change*, Vol. 35, 3, 304-333.

[40] Sen, A and T Smith, 1995, *Gravity Models of Spatial Interaction Behavior*, Springer-Verlag, Berlin and Heidelberg.

[41] Sheppard, E S, 1978, "Theoretical underpinnings of the gravity hypothesis", *Geographical Analysis*, 10, 4, 386-402.

[42] Sheppard, E S, 1984, "The distance-decay gravity model debate."In: Gaile GL, Willmott CJ (eds): *Spatial statistics and models*, Reidel Publishing Company.

[43] Sultana, S, 2002, "Job/housing imbalance and commuting time in the Atlanta metropolitan area: exploration of causes of longer commuting time", *Urban Geography*, 23(8), 728-749.

[44] Tiefelsdorf, M, 2003, "Misspecifications in interaction model distance decay relations: A spatial structure effect", *Journal of Geographical Systems*, 5, 25-50

[45] Tobler, W R, 1970, "A computer movie simulating urban growth in the Detroit region", *Economic Geography*, 46, 234-40.

[46] Wilson, A, 2010, "Entropy in urban and regional modelling: Retrospect and prospect", *Geographical Analysis*, 42, 364-394.

An experimental approach to study how commuting behaviour reflects preferences, labour market conditions and housing prices.

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Abstract

In this paper, an agent-based approach is used to generate spatial interaction data from a population that in a demographic sense is very similar the Norwegian. This approach allows us to perform controlled experiments on how a standard spatial interaction model replicates an observed trip distribution pattern. We demonstrate how the trip distribution depends on labour or housing market conditions, and how this is reflected in the estimates of the distance deterrence parameter. We also address the identification of how travel demand is affected by the preferences and different aspects of the budget constraint of the households. The results contribute both to ideas for modifications of the standard spatial interaction model, and to a reasonable interpretation of the distance deterrence parameter. The experiments for example demonstrate a tendency that the estimated distance deterrence parameter will be low if there are large wage disparities but low disparities in housing prices across the towns. Still, these are net effect of complex interactions, and the analysis demonstrates the demand for considering shopping, moving and commuting decisions simultaneously.

1 Introduction

As claimed by Fotheringham (1981), "the concept of distance-decay is an extremely important one in urban and economic geography". Most spatial interaction models incorporate a distance deterrence parameter, reflecting to what degree traffic flows are deterred by distance. In this paper we study the journeys-to-work, in a dynamic framework where moving is also an option

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for workers who want to improve their position. Still, the distance deterrence in commuting is estimated from a standard doubly-constrained gravity model, using information on origin-destination combinations from each specific year.

It is well known from the literature that standard spatial interaction models in general fail to account adequately for spatial structure characteristics. This leads to biased estimates of the distance deterrence parameter, and the interpretation of the parameter estimates will be due to a confusing mixture of the underlying traveling preferences and "the size and configuration of origins and destinations"of a geography (Fotheringham 1981, Lo 1991). The traditional interpretation of the parameter in terms of interaction behaviour was challenged in the 70s and the 80s. Important contributions to the debate can be found in Sheppard (1978, 1984) and in Fotheringham (1981, 1983a, 1983b, 1986). Tiefelsdorf (2003) claims that this problem did not receive much attention in the 90s "despite the fact that no satisfactory solution has been found".

The major bulk of the literature addressing this issue was depending upon a migration context. Commuting is in general studied in a doubly-constrained modelling framework, that is for a given spatial distribution of jobs and workers in a trip distribution perspective. It can be argued that the complex balancing factors involved in such a framework adequately capture relevant aspects of the spatial structure. However, it was demonstrated in Gitlesen and Thorsen (1998, 2000) that separate measures of spatial structure are relevant also in explaining the journeys-to-work. As an example, they successfully incorporated a measure of labour market accessibility, corresponding to the competing destinations model formulation of spatial interaction, that was introduced by Fotheringham (1983a). In agent-based experiments, Gholami et al. (2021) provided useful suggestions for modifications of a standard spatial interaction model, in how to explicitly incorporate relevant aspects of the geography.

In urban and regional economics, commuting is explained to result from a trade-off between traveling costs and housing prices. As in the Alonso-Muth model (Alonso, 1964 and Muth, 1969), this can be explained in a utility-maximizing framework. Assuming a monocentric geography with all jobs located in the cbd, the workers derive utility from housing and other consumption. Their optimal residential location then follows from maximizing utility, subject to budget restrictions.

The standard doubly-constrained gravity model is firmly founded in random utility maximization theory (Anas 1983, 1984), and it can also be derived from entropy maximization. In the latter context, the distance deterrence parameter can be interpreted to measure the impact on commuting flows of a marginal release in the cost constraint, see for example Wilson (2010). A sound theoretical foundation does of course not necessarily mean that all aspects of the local housing and labour markets are adequately represented in the standard model formulation. This paper employs an experimental design to demonstrate that there are some challenges in the model formulation as well as in the interpretation of parameter estimates. We also address problems related to the identification of how different aspects of the preferences, the housing market and the labour market affect spatial interaction behaviour. Are observed changes in interaction behaviour a response to preferences or incidents related to the budget?

Problems involving identification and endogeneity issues are potentially demanding in a pure empirical setting. The controlled experimental agent-based approach gets around such problems, since the microsimulations systematically introduce one exogenous change at a time, leaving no uncertainty concerning the direction of causation. The microsimulations generate new origin-destination matrices, and the standard gravity model is then used to estimate the distance deterrence parameter corresponding to the generated commuting pattern. This provides us with a useful tool for assessing the model and for interpreting parameter estimates. The procedure will be used to study how preferences, labour market conditions and housing prices affect the commuting pattern, and how this is reflected in the estimates of the distance deterrence parameter. We are equipped with utility functions, enabling us to distinguish between effects stemming from preferences and budget considerations. The results contribute to

- ideas for modifications of the standard spatial interaction model, into a model formulation that performs better in explaining the journeys-to-work in a region, and improves predictions related to specific shocks in labour market conditions, housing prices, or the transportation network.

- a reasonable interpretation of the distance deterrence parameter, in terms of how travel demand reflects preferences and budget constraints.

The experiments presented in this paper address issues related to the stability of parameter estimates both over time and across space. Stability over time is of course important if the model is used for predicting effects of for instance future changes in the transportation network.

If local O-D data are not sufficient for estimation, an option may be to use parameters estimates from other regions. However, as demonstrated in this paper, and in Gholami et al. (2021), parameter values should be expected to depend on the context in which they are estimated. The context is represented by spatial structure characteristics (Gholami et al. 2021), as well as labour market and housing market conditions. Hence, the results in this paper, and in Gholami et al. (2021), are useful both in evaluating the predicability and in making attempts to modify parameter values with respect to differences in spatial structure, housing and labour market conditions. This is an important motivation of our experiments.

In Section 2 we explain how the agent-based modeling framework is used to generate a synthetic population, involving both the geography, the demographics of the population, the spatial labour market interaction, the wage setting, and the supply and demand for housing. The standard doubly-constrained gravity model is briefly presented in Section 3. The benchmark scenario is defined in Section 4, while the results from the simulations and the estimation are presented in Section 5. We first study the impact on the distance deterrence pattern of variation in residential preferences, in Section 5.1, before we focus on labour market issues in Section 5.2, represented by spatial wage disparities, the level of the unemployment insurance benefit. The effect of variations in the costs of commuting is studied in Section 5.3. In Section 5.4, we discuss how the housing market pricing regime affects the spatial labour market interaction. Finally, concluding remarks are offered in Section 6.

2 The agent-based modelling framework

Agent-based modelling has been used in a wide number of applications, including physical, biological, social, and management sciences. In many cases, explaining complex patterns calls for explicit considerations of agent diversity (Kirman, 1992), rather than approximated by statistical averages (Page, 2011). According to Wilson (2010), we have a case of agent-based modelling when "the system of interest is populated by individual agents who are given (probabilistic) rules of behaviour". In this section, we explain the generation of a synthetic population of individuals, with randomly allocated preferences, a demography determined by Norwegian statistical data, and a set of rules concerning the functioning of the local labour and housing market.

The presentation of the agent-based modelling framework in this section is just a slightly abbreviated version of the presentation given in Gholami et al. (2021). Readers who are familiar with Gholami et al. (2021), or similar presentations of such an approach, may skip this section, and continue on to the sections defining a benchmark scenario and discussing the results. The motivation for including this section is that the paper then can be read and understood separately.

2.1 The geography

We consider a region with 12 towns. The distances between the towns can be varied continuously to investigate the impact of distance on the result of different experiments. The spatial configuration of towns is illustrated in Figure 1. The towns are separated into two groups, by the presence of a topographical barrier, like a lake, a fjord, or a mountain area. The towns A, B, C and D are located at on side of the barrier, while the other towns are located at the same side as zone E, which is the central business district of the geography. The long distance between towns A and G and between towns C and E are due to the topographical barrier.

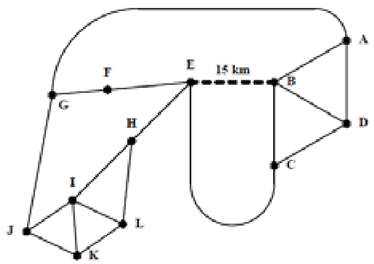


Figure 1: The spatial configuration of towns in the geography.

The distances between the towns in the geography are given by the following matrix:

$$\begin{bmatrix}
0 & 15 & 30 & 15 & 75 & 75 & 65 & 85 & 100 & 90 & 100 & 100 \\
15 & 0 & 15 & 15 & 60 & 70 & 80 & 70 & 85 & 95 & 95 & 85 \\
30 & 15 & 0 & 15 & 45 & 55 & 65 & 55 & 70 & 80 & 80 & 70 \\
15 & 15 & 15 & 0 & 60 & 70 & 80 & 70 & 85 & 95 & 95 & 85 \\
75 & 60 & 45 & 60 & 0 & 10 & 20 & 10 & 25 & 35 & 35 & 25 \\
75 & 70 & 55 & 70 & 10 & 0 & 10 & 20 & 35 & 35 & 45 & 35 \\
65 & 80 & 65 & 80 & 20 & 10 & 0 & 30 & 35 & 25 & 35 & 45 \\
85 & 70 & 55 & 70 & 10 & 20 & 30 & 0 & 15 & 25 & 25 & 15 \\
100 & 85 & 70 & 85 & 25 & 35 & 35 & 15 & 0 & 10 & 10 & 10 \\
90 & 95 & 80 & 95 & 35 & 35 & 25 & 25 & 10 & 0 & 10 & 20 \\
100 & 95 & 80 & 95 & 35 & 45 & 35 & 25 & 10 & 10 & 0 & 10 \\
100 & 85 & 70 & 85 & 25 & 35 & 45 & 15 & 10 & 20 & 10 & 0
\end{bmatrix}$$

2.2 Demographics

As for the two-node system used in McArthur et al (2010), the region gets populated by artificial heterogeneous, utility maximizing agents who are initially 15 years old and single. Each town has an initial probability to have people born in, and the system is allowed to evolve the initial population for 300 years. A set of statistical rules rules are introduced, which over 300 years are making up a population that is representative of the Norwegian population, wiping out all the traces of the initial population. The state of each agent contains information like gender, age, marital status, spouse, father, mother, children, house(s), address, work location, income, wealth and utility parameters which may change during a time-step. During one time-step (one month) agents can be born, marry, divorce, have children, apply for work, be retired, or die.

The rules in the model are as basically the same as in McArthur et al. (2010). Any adult woman can give birth with a probability conditional on age and marital status, and the sex of a child is determined randomly. If the woman is not married, the father is drawn randomly from the population of single men. Children are converted to adults when they reach the age of 15. At the age of 70, people are retired. Adults can marry, divorce, have children and apply for work. Mortality rates are based on standard life insurance tables, using Gompertz-Makeham's law i.e. that the death intensity of a man of age x is given by the function:

$$\mu = a + bc^x \qquad \text{where} \qquad a = 0.9, b = 4.4 \cdot 10^{-5} \text{ and } c = 1.10154$$

Death rates of women are adjusted by a 3 year age correction. Single agents can get married with the probability being conditional on age, sex and previous marital status. Spouses are drawn from the population of single people. It is reasonable to assume that the chance of two arbitrary people meeting is a declining function of the distance between the towns in which they live. The marriage probabilities are assumed to decline exponentially with distance:

$$\text{Max}\left[e^{-\sigma \cdot d}, 0.01\right]$$

Here, d is the distance between the towns and σ is a parameter representing the distance deterrence in marrying. The probability falls with distance, but never reaches zero, reflecting the fact that it is possible for two people to meet by chance irrespective of the distance between the towns in which they live. When a couple marries, they move in together along with any children they already have. Divorce rates are conditional on age and sex.

2.3 Preferences

Agents in the model act to maximize their utility. One obvious component of the indirect utility function is the wage. Workers consume their earnings and derive utility from this consumption. In a dynamic perspective, the life-time earnings is the relevant variable representing the consumption opportunities. In addition, the consumption opportunities depend on housing market transactions. Consumption and utility are derived from the life-time earnings, adjusted by the net real estate asset value. Let V_i denote the life-time earnings of individual i, plus the current value of the house, minus the price of the house at the point in time when it was acquired. Hence, V_i is a measure of the income that is disposable for consumption in a life-time perspective.

In addition to consumption in general, individuals are assumed to derive utility from housing consumption. In the version of the model used in this paper, the size of the house, H_i, is the only attribute accounted for. Housing prices vary across the geography, but within each town the housing price reflects only the number of squared meters of the house.

Like in the Alonso-Muth model of land use in urban economics (Alonso, 1964, and Muth, 1969), the utility function of individual i is then given by:

$$U_i(V, H) = V_i^{\alpha_i} H_i^{1-\alpha_i} \qquad 0 < \alpha_i < 1 \tag{1}$$

where α_i is the elasticity of the utility with respect to changes in life-time disposable income. In the experiments to be presented, we account for the possibility of individual variations in the preferences concerning the trade-off between consumption in general and housing consumption.

The housing market represents an important element in the development of a region, and it affects both decisions concerning spatial interaction, and the residential location pattern in the region. In the case of changes in the spatial distribution of jobs, commuting and migration represent two alternative responses of spatial interaction, with fundamentally different consequences for the population development of a specific town. Spatial disparities in housing prices affect the decisions to move or not, and the simultaneity between moving decisions and housing prices is accounted for in our agent-based approach.

2.4 Employment, and spatial labour market interaction

The agents in our model are assumed to be homogenous in terms of labour market qualifications. They apply for vacant jobs if this contributes to a net gain in utility for the household. Job applicants are randomly selected for the vacant job positions, and these who are employed may stay in the job until they retire. Unemployed agents receive an insurance payment.

If an agent accepts a job offer in an other town than, one form of spatial interaction is to move to the other town. If the agent is married, this requires that the sum of utilities of the spouses is increased by migration, accounting for changes in housing and other consumption. Alternatively, the agent will have to commute to the new job location, involving costs which are reducing the income disposable for housing and other consumption.

The production and employment in local sector firms is determined by demand originating within the region, these firms are serving the local population. The basic sector firms, on the other hand, are serving demand in other regions and countries. Basic sector production is assumed to be exogenously given, while local sector production is related to population size. In economic base theory, local sector employment in different towns is often assumed to be proportional to the local number of inhabitants. However, as argued and demonstrated in Gjestland et al. (2006), the density of local sector activities tends to be higher in the central business district (cbd), due to agglomeration economies. It is in particular customers in nearby towns who make their shopping in the cbd. This follows as an outcome of decisions based on comparing traveling cost to benefits in terms of lower prices and economies of scope in shopping. For towns located further from the cbd, the dominant part of the shopping takes place within the town. Hence, the local sector activities tend to be high in the cbd, low in suburban kind of towns, and close to the regional average in towns in a long distance from the cbd. Gjestland et al. (2006) developed a model explaining the local sector densities along this line of arguing. This model is integrated into our agent-based modeling framework, and parameterized as in McArthur et al. (2014, 2020).

The wage rate is set higher in the cbd than in the other towns initially. Wages tend to be higher in large and diverse job concentrations, reflecting "processes of learning, sharing, and matching"(Duranton and Puga 2004). For some of our experiments, wages are assumed to be exogenously given, with a given percentage increase all over the geography. In other experiments, we have introduced a Phillips curve style mechanism, like McArthur et al. (2010). Wages are adjusted by the local labour market situation:

$$w_j^t = 1.025 \cdot w_j^{t-1} \left(1 + \frac{U_j^t - U_j^{t-1}}{U_j^t}\right)^{-\lambda} \qquad \lambda > 0, j = 1, ..., 12 \tag{2}$$

where w_j^t is the wage level in town j in year t, and U_j^t is the unemployment rate in town j in year t. λ represents the sensitivity of wages to changes in the level of unemployment.

2.5 The housing market

The main contribution of this paper is to integrate the housing market and the labour market in a spatial context, where spatial interaction decisions reflect the spatial distribution of jobs and households, as well as spatial disparities in wages and housing prices.

The probability that moving is the utility-maximizing outcome is an increasing function of the commuting costs, and vice versa. Housing prices are affecting the moving decisions, as are employment and wage prospects. Commuting is a way to overcome the constraints from the housing market. Hence, the housing market is one of the determinants of the migration/commuting tradeoff. Many workers will for instance be unwilling to move from a town with low to a town with high housing prices, and prefer commuting as a response to attractive job offers from towns with high housing prices.

The housing prices are determined by the balance between demand and supply in the local housing market. This section offers a presentation of how housing demand and housing supply is integrated into the modeling framework.

2.5.1 Housing demand

The bidding procedure uses first-price sealed bid autions, in which all bidders submit their bids simultaneously, and the highest bid wins the auction. According to auction theory, see e.g. Krishna (2002), a Bayesian Nash equilbrium is obtained when bidder i has a valuation v_i and bids

$$\frac{N-1}{N} v_i,$$

where N is the number of bidders in the auction. The factor $\frac{N-1}{N}$ leads to significantly lower bids when N is small, and this effect appears to be crucial to get a reasonable price development in the housing market.

The factor is not meaningful if $N = 1$, and in our model we have instead used the factor $\max[\frac{N-1}{N}, \frac{1}{2}]$ to take that into account. Anticipation that in real world auctions, the number of bidders is not always very clear, we have used an adjustment

$$0.2 + 0.8 \max \left[\frac{N-1}{N}, \frac{1}{2} \right],$$

taking into account that that bidders may sometimes fear that slightly more people might be interested in bidding, and are hence placing a slightly higher bid. This reduces the strength of the factor to 80% of its original strength.

At each time-step the agents make random checks to evaluate their position. If this check is successful, the agent enters the housing market and places a bid on the most favorable option. The winning bid is inspected by the seller and a sale is carried out if the winning bid exceeds his or hers reservation price. The details are technical and we refer to Gholami et. al (2021) for more information on the bidding procedure.

2.5.2 Housing supply

The willingness to pay for housing at different locations is reflecting the individual preferences, and the spatial distribution of wages and job opportunities. However, regional and local housing prices are of course not solely determined by such demand factors. The regional and local housing supply also has to be accounted for. Our experiments starts with an initial supply of housing, that is distributed across the zones according to rules defined by the "system administrator", that is a regional government planning entity.

As a general rule, new houses are built according to a frequency of 5% yearly. This frequency is a minimum for the different towns in the region. Still, the frequency is allowed to vary systematically across the zones. If a zone experienced a high demand and a correspondingly high increase in housing prices in the previous year, then this is allowed to be reflected in a high building frequencies of new houses, provided by either public or private agents.

$$HS_j^t = \begin{cases} HS_j^{t-1} \cdot 1.05 \cdot \left(\frac{P_{hj}^{t-1}}{P_{hj}^{t-2}}\right)^{\gamma} & \text{if} \quad \frac{P_{hj}^{t-1}}{P_{hj}^{t-2}} > 1.05 \\ 1.05 & \text{otherwise} \end{cases}$$

where HS_j^t and P_{hj}^t are the housing supply and the housing price per m^2 in town j in year t. γ is the elasticity of housing supply w.r.t. the price increase observed in the previous year. The model is not explicit w.r.t. whether new houses are provided by public or private agents.

3 The distance deterrence parameter in a standard doubly-constrained gravity model of commuting

The agent-based modelling approach is used to generate origin-destination matrices, which are next used for the estimation of the distance deterrence parameter from a standard doubly-constrained gravity model. A standard formulation of a doubly-constrained gravity model is:

$$T_{ij} = A_i O_i B_j D_j \exp(-\beta d_{ij}) \tag{3}$$

$$A_i = \left[\sum_j B_j D_j \exp(-\beta d_{ij})\right]^{-1} \tag{4}$$

$$B_j = \left[\sum_i A_i O_i \exp(-\beta d_{ij})\right]^{-1} \tag{5}$$

where:

T_{ij} is the estimated number of travellers from origin i to destination j, $i, j = 1, ..., n$

O_i is the observed number of trips originating from zone $i = 1, ..., n$

D_j is the observed number of trips destinating in zone $j = 1, ..., n$

d_{ij} is travelling time by car, from origin i to destination j; $i, j = 1, ..., n$

β is a distance deterrence parameter. A_i and B_j are the balancing factors that ensure the fulfillment of the marginal total constraints; $\sum_j T_{ij} = O_i$ and $\sum_i T_{ij} = D_j$. Consequently, this doubly-constrained model specification is constructed for a pure trip distribution problem. For a discussion of the theoretical foundation of this model, see for example Sen and Smith (1995).

As mentioned in the introduction, this standard doubly-constrained gravity model fails to account adequately for spatial structure characteristics, leading to biased estimates of the distance deterrence parameter. Some of this literature is also reviewed in Tiefelsdorf (2003), who in addition demonstrate how a proper model specification is of paramount importance in interaction modeling. Accounting for relevant characteristics is of course important for producing unbiased parameter estimates, as well as for making reliable predictions, for instance on interregional transferability problems (see for instance McArthur et al. (2011)). There is evidence in the empirical literature that many characteristics of the spatial structure are not captured by the balancing factors, see for example Gitlesen and Thorsen (1998, 2000).

It was also mentioned in the introduction that the standard doubly-constrained gravity model does not capture all relevant aspects of the local housing and labour markets, which are influencing the budget constraint in the utility maximizing problem. This paper focuses on how such aspects affect the estimates of the distance deterrence parameter, and also on how the parameter reflects both the underlying preferences and the budget constraint of the workers

4 Defining a benchmark scenario

A benchmark scenario is defined as a starting point for introducing different kinds of exogenous shocks to the system. One exogenous shock is considered at a time, to evaluate the effect of such shocks on the parameter reflecting the distance deterrence in spatial labour market interaction. The complexity of the problems to be discussed rules out pure analytical, comparative static, approaches, but the controlled experiments to be discussed are as close you can get to such approaches.

In our benchmark scenario, the cbd (zone E) is allocated 5 times more of the initial population than the other towns, as are the initial houses. As defined by Norwegian average rates of marrying, births, deaths, etc., the members of this population then interact over 300 years, generating a population that mirrors the Norwegian in terms of demography. After this initialization, the labour and housing markets are introduced, which are then influencing how jobs and households are distributed across the towns in the simulation experiments. Our benchmark scenario is defined by running the model for another 50 initializing years, for given values of all exogenous variables and parameters. However, this scenario is no steady-state equilibrium. The population is continuously changing, as some inhabitants die, new are born, etc. Still, in our benchmark scenario, the system has reached a kind of a dynamic equilibrium, where none of the endogenous variables seem to be in a significant trend.

Based on this benchmark scenario, we introduce a number of experiments by changing for example some labour market conditions, and then run the system for another 15 years. However, for some cases it makes limited sense to introduce changes at a specific point in time. This applies for example for different scenarios of the underlying preferences. For such fundamentally sluggish changes, it can be argued to make more sense to study differences in response by repeating the 50 years of initialization. Our benchmark scenario is defined by a set of values of the parameters characterizing individual preferences, the housing market, the labour market, and the terms of intraregional commuting. The mechanisms and parameter values are as follows:

Preferences. $\alpha_i \in (0.3, 0.7)$, defines the interval in which the individual weight put on general consumption is allowed to vary; randomly and uniformly distributed;

Housing market. Housing demand is derived from utility-maximizing behaviour of individual households weighing housing consumption against consumption in general, adjusted for commuting costs. After the initialization, new houses in the different towns are provided according the mechanism described in Section 2.5.2, with a housing supply elasticity $\gamma = 1$. The initial price of building a house is 5000 per square meter, and the housing price construction price increases by 1% per year. It takes 1 year to construct a house.

The spatial distribution of local and basic sector jobs. The local sector employment is assumed to be 20% of total population in the region, distributed across the towns according to the model that was presented in Gjestland et al. (2006), see Section 2.4, using the same parameterization as in McArthur et al. (2014, 2020). The spatial distribution of basic sector jobs is presented in Table 1. No attempts have been made to account explicitly for spatial differences in entrepreneurship and different kind of agglomeration economies, etc.

Wages The yearly wage in year 0 is assumed to be NOK 100000 in all the zones except the cbd, zone E, where it is assumed to be NOK 115000. This reflects higher efficiency in thick labour markets, as explained in Section 2.4. The unemployment insurance is set to be NOK 60000 in all the zones in year 0. Both wages and the unemployment insurance are assumed to increase by 2.5% yearly, but as explained in Section 2.4, local wages are adjusted by a Phillips curve style mechanism, with $\lambda = 0.1$. In addition, the income disposable for consumption on housing and other goods are reduced by a 28% income tax, while mortgages and life-time incomes are calculated by the use of a discount rate of 2.5%.

Commuting costs The generalized round-trip commuting costs are assumed to be NOK 0.6 per kilometer in year 0, incurred over 200 working days per year. The commuting costs are increasing by 2.5% per year.

The chosen size of the system is a compromise between commuting time and the call for robust relationships between the variables. In Table 1, $BASE_j^t$, POP_j^t, and TOT_j^t are, respectively, the number of basic sector jobs, the population, and the total number jobs in town j in year t. Table 1 offers information on where the given initial distribution of basic sector jobs takes the system after 50 years of interaction. The most striking development has been in the housing prices of the cbd, town E. This is explained by the fact that the cbd has a high concentration of jobs in the geography, and higher wages than the other towns, which results in a very high demand for housing in the cbd. In nominal terms, the wage disparities between the cbd and the other towns have increased over time, but the relative difference has remained at approximately the same level.

Table 1: Zonal values of basic variables in the benchmark scenario

zone	$BASE_j^0$	POP_j^{50}	TOT_j^{50}	U_j^{50}	P_{hj}^{50}	w_j^{50}
A	430	2 049	830	8.1%	23 863	329 940
B	270	1 750	603	7.9%	24 354	318 676
C	220	1 604	507	8.8%	24 332	321 420
D	60	1 894	420	9.7%	22 985	309 731
E	2 200	3 139	4 491	9.3%	101 361	369 140
F	350	1 545	472	10,0%	24 817	314 013
G	310	1 857	575	10,8%	25 048	310 418
H	460	1 703	594	10.4%	24 853	314 425
I	100	1 288	284	10.1%	24 743	302 884
J	330	1 623	598	10.8%	23 467	305 140
K	350	1 683	628	9.3%	23 480	307 777
L	60	1 431	264	10.3%	23 811	320 838
Region	5 140	21 566	9 679			

5 Results of experiments with preferences, housing prices, wages, and commuting costs

We are monitoring how preferences and the housing and labour market conditions affect spatial interaction. Our agent-based procedure is analogous to comparative static approaches in a pure analytical framework, focusing on the impact of partial changes in an exogenous variable on a set of endogenous variables. However, our modeling framework is dynamic rather than static. Agents make decisions based on life cycle considerations, and the system changes continuously as a response to numerous independent individual decisions.

In interpreting the results, keep in mind that the analysis is based on a set of simplifying assumptions. One is that we have abstracted from worker and job heterogeneity. Still, the curves in most of the figures to follow reflect the outcome of very complex mechanisms, like the competition for jobs and houses, for households which tend to have more than one worker.

5.1 Varying preferences

As mentioned in Section 2.3 the choice between housing consumption and other consumption is determined from preferences and disposable income. The disposable income is the discounted present value of all current and future incomes, with a deduction of taxes and commuting costs. The preferences are represented by the parameter α_i in Equation 1, that is reflecting the individual weight put on housing consumption and other consumption.

The estimates of the distance deterrence parameter in commuting depends on value attached to α_i in the utility function of the households. In our benchmark scenario, the parameter value attached to the two attributes in the utility function is allowed to vary randomly within the interval (0.3-0.7). This is corresponding to a neutral situation. In the case where we consider a substantially higher value of the weight attached to other consumption in the utility function, values are allowed to vary randomly in $\alpha_i \in (0.8, 0.9)$. This corresponds to preferences where less weight is put on housing, and more on other consumption. A low α takes values of $\alpha_i \in (0.1, 0.2)$.

Intuitively, it may seem to be a reasonable hypothesis that a higher value of α will lead to a labour market solution with less commuting and smaller houses, making room for more other consumption. A lower degree of spatial labour market interaction corresponds to the hypothesis that the estimated distance deterrence parameter will be higher than in the situation with more neutral preferences in favour of other consumption, ceteris paribus. Correspondingly, it seems like a reasonable hypothesis that a situation with preferences more directed towards housing and less towards other consumption, results in more commuting and a lower estimated value of the distance deterrence parameter than in the benchmark scenario.

These hypotheses are not supported by our experiments. Figure 2 provides an illustration of estimated values of the distance deterrence parameter for different interval levels of the parameter α_i in the utility function. The values of $\hat{\beta}$ are lowest in the case where individual α_i-values are randomly drawn from an interval consistent with strong preferences for funds available for other consumption. Hence, the demand for low commuting expenses does not seem to be a dominating factor for workers' choice of a residential-workplace combination.

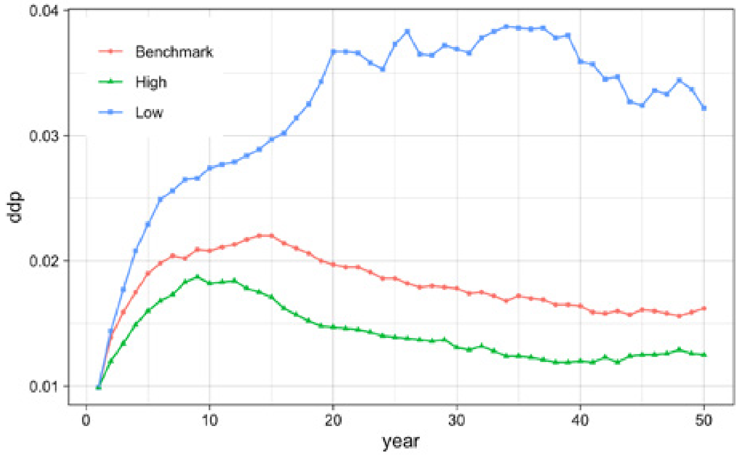
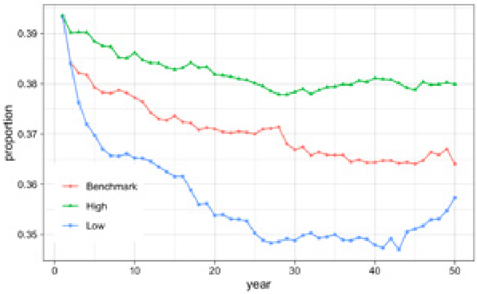
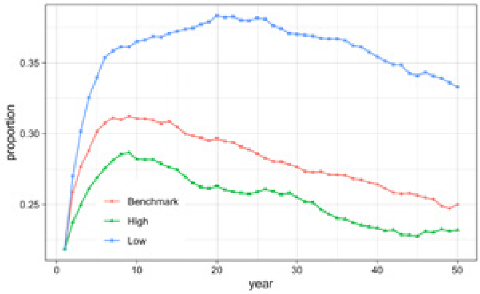


Figure 2: Estimates of the distance deterrence parameter in cases with high ($\alpha_i \in (0.8, 0.9)$) and low ($\alpha_i \in (0.1, 0.2)$) values attached to other consumption, V_i, in the utility function. In the benchmark scenario, $\alpha_i \in (0.3, 0.7)$.

The hypotheses introduced above do not account for the effect of spatial variation in wages. First, there are some relatively minor spatial wage disparities resulting from the Phillips curve style mechanism. However, the main source of spatial wage disparities is the high wage in the cbd, which is reflecting agglomeration economies. With a high α_i in the utility function, workers are more attracted to high-wage jobs. This means that workers to a larger degree apply for jobs in the cbd. Even if their residences are in a relatively long distance from the cbd, the wage increase more than compensate the counteracting increased commuting expenses following from working in the cbd rather than locally. As illustrated in Figure 3, higher values of α_i's contribute to attract more commuters to the cbd, and to the tendency that workers are less inclined to accept job offers in the town where they live. Hence, spatial labour market interaction is more responsive to spatial wage disparities, and this is dominating the increased demand for low commuting expenses that is resulting when other consumption is given a strong weight in the utility function. Part b) of Figure 3 demonstrates that high values of α pull in the direction of labour market solutions with no commuting.



a) In-commuters to the cbd



b) Non-commuters

Figure 3: The proportion of workers who are living in other towns, while working in the cbd, and the proportion of workers who are living and working in the same town. Cases with high and low values of the α_i parameter in the utility function are compared to the benchmark scenario.

5.2 Labour market issues

As a first experiment related to the labour market, we ignore the likely presence of different kinds of agglomeration economies, which means that we ignore the the possibility that wages are higher in the large, thick, local labour market in the cbd. Hence, this experiment start by assuming that wages are equal all over the geography in year 0, rather than being 15% higher in the cbd. In both cases, however, we allow for Phillips curve style adjustments to account for changes in balance between local demand and supply over the 50 year long period to follow.

As illustrated in Figure 4, the distance deterrence effect in commuting is estimated to be considerably higher in the case with no spatial wage disparities initially. The discussion above has demonstrated that the wish for low commuting expenses are often traded off against the possibility of high wages in other towns. With no spatial wage disparities, the wish for low commuting expenses becomes the dominating force in the spatial labour market behaviour of

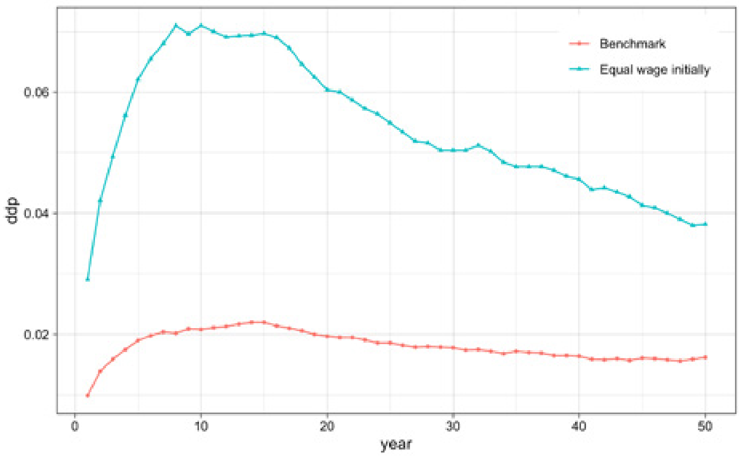
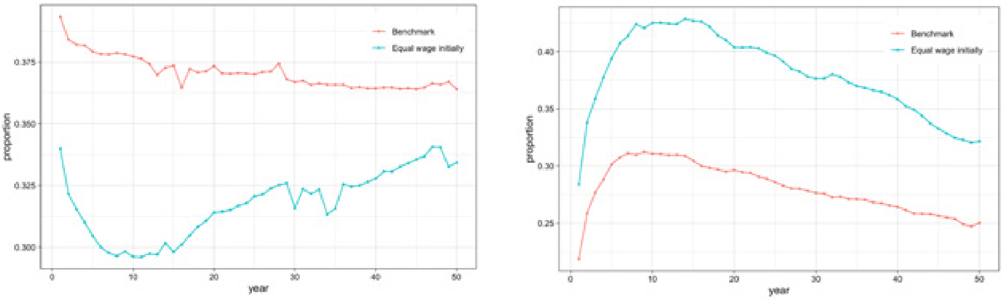


Figure 4: Estimates of the distance deterrence parameter in the benchmark scenario and a situation where wages are equal all over the geography in year 0.

workers. This is reflected in Figure 5b, where workers in the early initializing years search for combinations of job and residence which are not involving commuting. This corresponds to the tendency of increasing estimates of $\hat{\beta}$ in this period, as illustrated in Figure 4.

Eventually, the development towards less commuting is culminating in this dynamic system. Workers are retiring from the labour market, being replaced by new workers, and the fact that most households have two workers causes some friction in commuting pattern. The cbd is still a centrally located residential location, with a high concentration of jobs attracting many workers. However, this contributes to higher housing prices in the cbd than elsewhere in the geography. As a result, there will be an increasing tendency that workers prefer commuting rather than moving into the cbd. In addition, wages are adjusted in favour of towns with low unemployment and a high demand for jobs. In year 50 of this case, the wage in the cbd is 4.4% higher than the average wage level in the region.

Both the response in housing prices and wages contribute to explain the tendency of increased in-commuting to the cbd that is illustrated in Figure 5a. At the same time, such mechanisms contribute to explain the falling number of non-commuters (Figure 5b) and the tendency that the estimates of the distance deterrence parameter is reduced over time, as illustrated in Figure 4. Still, the experiment demonstrates that small spatial wage disparities cause low commuting to the cbd, a high number of non-commuters, and commuting flows resulting in high estimates



a) In-commuters to the cbd b) Non-commuters

Figure 5: The proportion of workers who are living in other towns, while working in the cbd, and the proportion of workers who are living and working in the same town. The benchmark scenario is compared to a case where wages are equal in all towns in year 0.

of the distance deterrence parameter.

As another aspect of the labour market, we have also run an experiment with a substantially higher unemployment benefit than in our benchmark scenario. In all the other experiments, the unemployment benefit is around 60% of the wages. In our agent-based approach, workers are in some sense relatively homogeneuous, for instance in their working attitude. They make rational decisions, based on their utility functions, where the prospects of housing and other consumption is determining their choices. Working is not causing any inconvenience, for instance in terms of lost time for leisure activities. This means that even if unemployment benefit is considerably increased, for instance to 80% of the wages, this will not affect the individual choices, unless the difference between the wages and the unemployment benefit is exceeded by the commuting expenses for a worker. Since commuting expenses are in general not of this size, the economy is predicted to be only marginally affected by an increased unemployment benefit.

In the real world, workers may be heterogenous in their work ethic, and how they consider work in itself. Some may find work inconvenient, as a negative element in the utility function. Rather than introducing a modified utility function, assume that this inconvenience cost is added to the increased unemployment benefit, to represent an increased opportunity cost of choosing to work. To test the effect of increased unemployment benefit, we take it into the extreme, by letting the sum of the unemployment benefit and the inconvenience cost equal the wage level in the town with the second lowest wage level in year 50 of the benchmark scenario.

The effect of this experiment on the estimates of the distance parameter is illustrated in

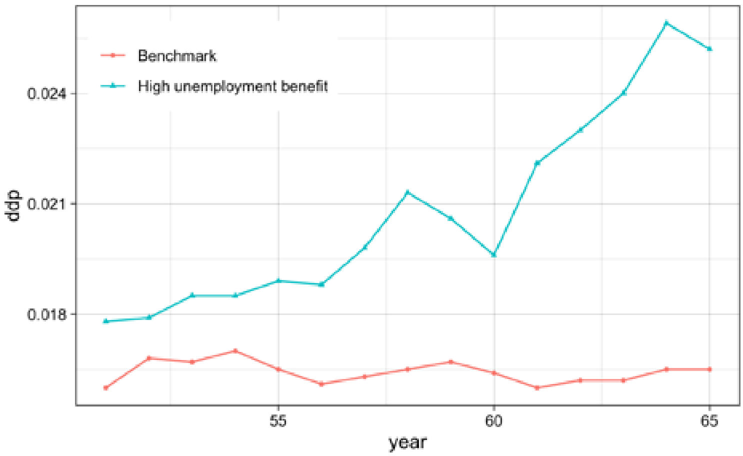


Figure 6: Estimates of the distance deterrence parameter in the benchmark scenario and after a substantial increase in the unemployment benefit (including an inconvenient costs of working).

Figure 6. The intuitively reasonable conclusion is that a higher unemployment benefit pulls in the direction of a higher estimate of the distance deterrence parameter. At the end of the 15 years period after this shock was introduced, the level of unemployment has risen to around 30%. As a result of the Phillips curve mechanism, the increased level of unemployment was accompanied by an unfortunate wage development. In fact, the unemployment benefit was higher than the wage level in all towns except the cbd in year 65.

This may seem a bit unrealistic. In the real world, the unemployment insurance benefit hardly would be allowed to be continuously increased by 2,5% annually in such a scenario. In addition, workers should in general be expected to respond more instantaneously to the increased unemployment benefit. In our agent-based modeling approach, the workers do not reconsider their job and residential location continuously. According to the procedures which are specified in the program, it takes around 10 years before all the workers have considered their current situation up against other alternatives, like choosing not to work. This is introduced as a natural kind of friction, corresponding to an idea that most people are content with their current situation, without considering changes. Still, this can be argued to change as a result of the shock, redefining the rules of the game. It is of course possible to increase substantially the proportion of the population that is checking for better alternatives at a specific point in time. This would speed up the process towards a new dynamic kind of equilibrium state, at the expense of increased computing time.

Despite these objections, Figure 6 provides a reasonable prediction to which direction increased unemployment benefits affects the estimates of the distance deterrence parameter. As times go by after the shock, only the cbd has job opportunities which offer a reasonable compensation for commuting expenses and work inconvenience. Over the 15 year long period that is considered in Figure 6, there is a marked increase both in the number of non-commuters, the number of unemployed, and in the commuting into the cbd. At the same time, in particular long-distance commuting between the other towns has become less attractive, and considerably reduced. This is reflected in the higher estimates of the distance deterrence parameter. As discussed above, the scenario underlying Figure 6 is in some sense extreme. The same effects could be illustrated in a more realistic scenario, by including more heterogeneity between agents, for instance in terms of inconvenience costs related to working.

5.3 Commuting costs

An increased commuting cost affects the disposable income which is available for housing consumption and other consumption. If commuting costs are high, then households are expected to be more concerned with living close to their workplace, opening for attractive combinations of housing consumption and other consumption. At the same time, this has an impact on housing prices, both in towns with an abundant supply of jobs, and in towns with a shortage of jobs for the local workers. This may in effect push some households towards residential locations with a high risk of inflicting longer commuting for a household member.

Figure 7 demonstrates the effect on the estimated distance deterrence parameter of changes in the commuting expenses occurring in year 50. The benchmark scenario is compared both to a situation with 50% higher and a situation with 50% lower commuting costs.

Gholami et al. (2021) study the effects of a proportional change in all distances. By comparison, the results of changing the distances by for example 50% are substantially different from changing the commuting costs correspondingly. One obvious question is why the results of these seemingly equivalent experiments are not the same. First, in comparing the two scenarios, they do not cover the same time periods. It makes more sense to introduce changes in commuting expenses at a specific point in time than it does for changes in physical distances. Hence, the

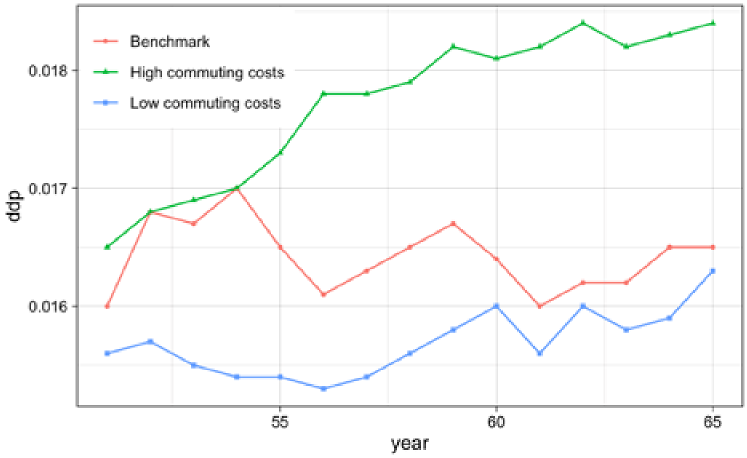


Figure 7: Estimates of the distance deterrence parameter in the benchmark scenario and in situations where the commuting costs increased and decreased by 50% in year 50.

changes in commuting expenses are introduced in year 50, while Gholami et al. (2021) illustrate scenarios where distances differ from the beginning, in year 0.

This difference in time perspective does not obscure that a reduction in commuting expenses has an impact on $\hat{\beta}$ that differs substantially from the estimates following from a situation with corresponding reductions in the distances between the towns. As demonstrated in Gholami et al. (2021), a compact system, with short distances between the towns, results in higher $\hat{\beta}$'s than the benchmark scenario, while it follows from Figure 7 that a reduction in commuting expenses pulls in the direction of lower $\hat{\beta}$.

This latter result is more according to a priori expectation than the results following from a more compact system, with short distances between the towns. Intuitively, it makes good sense that a reduction in commuting expenses leads to more commuting between the towns, and a reduced estimate of the distance deterrence parameter. Recall from Section 2.4, however, that reduced distances lead to a substantial relocation of local sector jobs, in favour of the cbd. With lower distance, households in other towns do more of their shopping in the cbd, benefitting from different kinds of agglomeration economies in shopping.

In this agent-based modelling framework, the LSD-function is related to euclidean distances rather than to commuting expenses. This is the basic reason for the differences in the $\hat{\beta}$'s between the two scenarios. The euclidean distances between towns is a characteristic of the spatial structure, while commuting expenses merely represents the terms of traveling. It can of course be argued that the terms of traveling are equally relevant for shopping. To the degree that the spatial distribution of local sector activities are explained by shopping behaviour, reduced traveling expenses should have the same kind of effect on the LSD that lower euclidean distances. However, it may be reasonable to distinguish between commuting and other forms of spatial interaction with respect to traveling expenses. The reduction in commuting expenses may be due to the introduction of an arrangement where such expenses are tax deductible, like in the Norwegian tax system. The experiment with an increase in commuting expenses can be justified by the introduction of congestion pricing during peak hours.

Hence, it is possible to make sense of a case where the spatial distribution of local sector activities responds to differences in euclidean distances, but not to changes in commuting expenses. Gholami et al. (2021) demonstrated that the effect of a change in euclidean distances can be separated into an effect of different commuting expenses and an effect of the resulting differences in the spatial distribution of job opportunities. The experiment underlying the results illustrated in Figure 7, can be motivated to uncover the two effects. By comparing Figure 7 to the results presented in Gholami et al. (2021), it follows that variations in commuting expenses have a relatively modest impact on $\hat{\beta}$.

5.4 The housing market

It is well known that a reverse causality can be expected for the relationship between migration flows and housing prices. This also means that housing prices can be expected to influence commuting flows. All the results that are presented above, are potentially influenced by variations in the housing prices. This means that the estimates of β potentially reflect the housing market mechanism. To examine this hypothesis, we turned off this mechanism, in effect not allowing for spatial variation in house prices. House prices are increased by the inflation rate in all the towns, which means that the house prices are persistently equal all over the geography, rather than being locally set by the market. We then re-estimated β. This experiment is run for a case with alternative locations of the cbd, that is in comparing the situation where town E is the cbd to a situation where town B is the cbd. Other aspects of this case was discussed in Gholami et al. (2021). The results of the housing market experiment are presented in Figure 8.

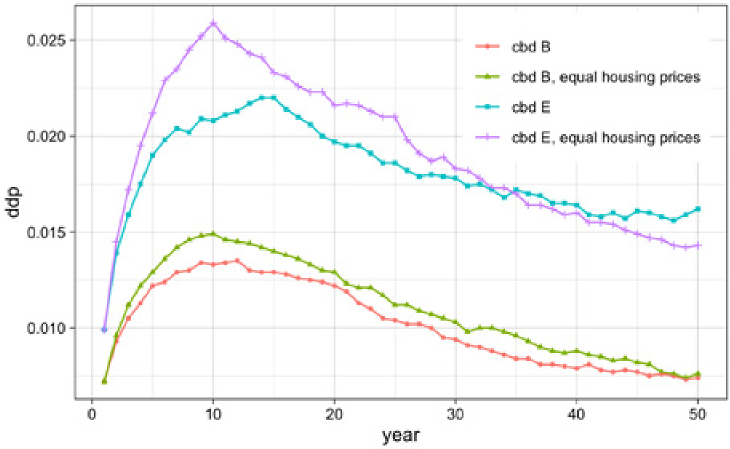


Figure 8: Estimates of the distance deterrence parameter for alternative locations of the cbd and alternative regimes of house pricing.

As demonstrated and discussed in Gholami et al. (2021), the estimated value of β is lower if the cbd is located in the least populous area, that is if town B, rather than town E, is the cbd. According to Figure 8, this will also be the case if the house price mechanism is turned off.

It appears from Figure 8 that the housing price mechanism has no significant impact on the estimated β. As a first inclination, this may come as a surprise. It is in the very heart of the standard bid-rent theory, that was introduced by Alonso in the 60s, that residential location decisions are represented by the trade-off between housing prices and commuting costs to the regional centre, which is hosting attractive job opportunities. This theory to a large degree explains the population growth in suburban areas, and in the more peripheral areas of a labour market region. The residential suburbanization coincides with increased commuting into the cbd, and this should be expected to contribute to a low $\hat{\beta}$.

If the housing prices mechanism is turned off, with no spatial variation in housing prices, then residing in the cbd should be expected to be more attractive. High wages and low commuting costs then contribute to high consumption and a high level of utility for the households residing in the regional center. Hence, the hypothesis is that more people live and work in the cbd if housing prices are not allowed to vary over the geography. This hypothesis is supported in Figure 9a. The absence of a housing price mechanism contributes to prevent the decreasing tendency to live and work in the cbd that would evolve if relative housing prices were allowed to increase in the cbd as time passes by.

Why does not this tendency to work and live in the cbd coincide with higher estimates of β, reflecting a reduced tendency of commuting? The fact that more people are living in the cbd has an impact on the clustering of local sector jobs. As explained in Section 2.4, our agent-based approach accounts for agglomeration economies in shopping. This is explaining why high concentrations of residents living in, and close, to the cbd, attracts local sector firms to the cbd. Consider first the two standard cases in Figure 9b, where housing prices are allowed to increase more in the cbd than elsewhere in the geography. It follows from the figure that the proportion of local sector jobs which is located in the cbd is decreasing as people are moving out from the cbd when housing prices are increasing. This decrease in the number of local sector jobs in the cbd is prevented in cases where the relative housing prices are constant across the geography.

This means that ruling out spatial adjustments of housing prices has two opposing effects on commuting flows:

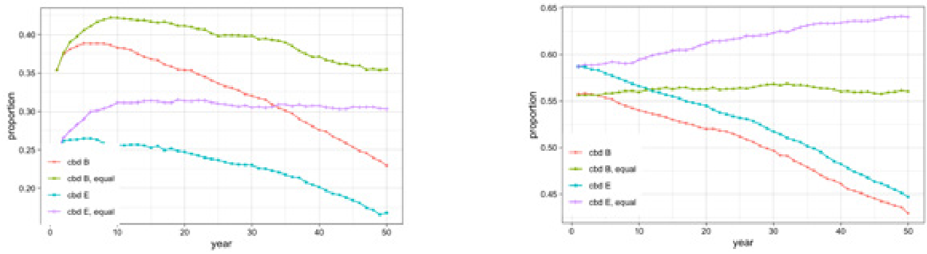
a) more people work and live in the cbd

b) there will be more commuters into local sector jobs in the cbd

The result that estimates of β are only marginally influenced by the housing price mechanism does not mean that commuting flows are not affected. One effect of ignoring spatial variations in housing prices is that more people choose to work and live in the cbd, rather than commuting. This pulls in the direction of a high value of β. Another effect is that a high concentration of people living in the cbd is attracting a high number of local sector firms, and therefore a high number of in-commuters to the cbd. This pulls in the direction of a low value of β. Figure 8 indicates that these two effects are approximately cancelling each other out, resulting in a relatively insignificant total effect on the parameter estimate.

6 Concluding remarks

In this paper, an agent-based approach is used to generate spatial interaction data from a population that in a demographic sense is very similar the Norwegian. This approach allows us to perform controlled experiments on how a standard spatial interaction model replicates an observed trip distribution pattern. This further enables us to discuss potential sources of biased



a) Live and work in the cbd

b) Local sector jobs in the cbd

Figure 9: The proportion of the workers in the region who live and work in the cbd, and the proportion of local sector jobs in the region which is located in the cbd, for alternative locations of the cbd. Two regimes of house pricing: on with equal prices in all towns, another where house prices are set by the market and allowed to vary across the towns.

parameter estimates, causing errors in predicting how for example commuting flows respond to specific exogenous changes in the terms of traveling.

The main ambition of the paper is to find how the housing and labour market conditions may influence the performance of a spatial interaction model. Travel demand in general reflects the outcome of a utility-maximizing problem, involving both the preferences and the budget constraint of the agents. The agent-based approach allows for distinguishing between effects originating from preferences and from budget considerations. Labour and housing market conditions influence the decisions through the budget, and we used the experimental design to focus on how in particular the estimates of the distance deterrence parameter in commuting reflect features of the labour market, the housing market and the underlying preferences.

Table 2 summarizes some of the results. For each experiment, the table reports the estimates of the distance deterrence parameter, a measure of model performance, and the coefficient of variation of the jobs/housing balance (J/H) in the 12 towns of the geography. Model performance is measured by the standardized root mean square errors (SRMSE), which is a frequently used measure for replicating a data set of a spatial system. It is a reasonable hypothesis that substantial variation in J/H between the towns corresponds to a system with considerable commuting, which may be reflected in low estimates of the distance deterrence parameter.

According to Table 2, the estimates of the distance deterrence parameter from a standard gravity model vary substantially with respect to the underlying individual preferences for housing consumption and other consumption, and to the labor and housing market conditions. This is a demonstration that both the spatial variation in wages and housing prices, the unemployment

Table 2: Parameter estimates, model performance, and the coefficient of variation (CV) of the jobs/housing (J/H) balance between the towns in different experiments. All values are calculated for the last year of each experiment

	$\hat{\beta}$	SRMSE	J/H balance, CV
Benchmark	0.0162	0.4250	0.3270
$\alpha_i \in (0.1, 0.2)$	0.0322	0.6311	0.2969
$\alpha_i \in (0.8, 0.9)$	0.0125	0.4124	0.4292
Equal wages initially	0.0382	0.3025	0.3790
High unemployment benefit	0.0252	0.7744	0.5257
High commuting cost	0,0184	0.4594	0.3101
Low commuting cost	0.0163	0.4093	0.3140
Equal housing prices, CBD E	0.0143	0.4241	0.8862
Equal housing prices, CBD B	0.0076	0.4921	0.6747

insurance benefit, and the level of commuting costs, affect the travel demand, which is reflected in the estimates of the distance deterrence parameter. It follows from Table 2 that $\hat{\beta}$ can be expected to be high in a geography where:

- the inhabitants care much about housing consumption, and less about other consumption
- there are not large spatial wage disparities
- there are large spatial housing price disparities
- the commuting costs are high
- there is a high unemployment insurance benefit

However, the results reported in Table 2 represent the net effect of several forces, in some cases pulling in different directions. As was clear from the discussion in Section 5, commuting decisions should be considered simultaneously to decisions on shopping and moving in an interpretation of how exogenous changes affect the commuting pattern in the geography. A partial perspective in interpreting spatial interaction data is often inadequate. The discussion and the results also suggest that measures of disparities in wages and housing prices should be considered explicitly incorporated in a model explaining commuting flows. Introducing the generalized costs of commuting, incorporating cost elements, rather than the euclidean distances also contributes to a better explanation of commuting. Such modifications potentially improve the model for predicting the effects of exogenous changes in housing and/or labour market conditions, and for making the transferability of parameter estimates more reliable, in time and space.

According to Table 2, the standard gravity model performs best in cases with only minor spatial wage disparities, while it is not very reliable in the case with a very high unemployment insurance benefit, and in the case where workers primarily are concerned about living in large houses. The results in Table 2 also indicate a tendency that cases with an unbalanced jobs/housing distribution across the towns generate a lot of commuting, and correspondingly lead to low values of $\hat{\beta}$. However, a more detailed discussion of the J/H balance is beyond the scope of this paper, and left for future research.

References

[1] Alonso, W, 1964, “Location and land use: towards a general theory of land rent; Harvard University Press: Oxford University Press, London.

[2] Anas, A, 1983, “Discrete choice theory, information theory and the multinomial logit and gravity models”,*Transportation Research B*, 17, pp. 13-23.

[3] Anas, A, 1984, “Discrete Choice Theory and the General Equilibrium of Employment, Housing, and Travel Networks in a Lowry-Type Model of an Urban Economy”, *Environment and Planning A*, 16, 1489-1502.

[4] Duranton, G and D Puga, 2004, “Micro-foundations of urban agglomeration economics”, in Henderson J V and J F Thisse, Handbook of regional and urban economics 4.

[5] Fotheringham A S, 1981, “Spatial structure and distance-decay parameters”, *Annals of the Association of American Geographers*, 71, 425-436.

[6] Fotheringham A S, 1983a, “Some theoretical aspects of destination choice and the relevance to production-constrained gravity models”, *Environment and Planning A*, 15, 1121-1132

[7] Fotheringham A S, 1983b, “A new set of spatial interaction models: the theory of competing destinations”, *Environment and Planning A*, 15,15-36.

[8] Fotheringham A S, 1986, “Modelling hierarchical destination choice”, *Environment and Planning A*, 18, 401-418.

[9] Gholami, A A, I Thorsen and J Ubøe, 2021, "An agent-based approach to study spatial structure effects on estimated distance deterrence in commuting", unpublised report, available upon request.

[10] Gitlesen J P and I Thorsen, 1998, "Empirical Evaluation of Alternative Model Specifications to Predict Commuting Flows", *Journal of Regional Science*, 38, 2, 273-292.

[11] Gitlesen J P and I Thorsen, 2000, "A Competing Destinations Approach to Modeling Commuting Flows: A Theoretical Interpretation and An Empirical Application of the Model", Environment and Planning A,

[12] Kirman, A P, 1992, "Whom or what does the representative individual represent?" *Journal of economic perspectives*, 6(2), 117-136.

[13] Krishna, V, 2002, *Auction Theory*, San Diego, USA: Academic Press

[14] Lo L, 1991, "Spatial structure and spatial interaction: a simulation approach", *Environment and Planning A*, 23, 1279-1300

[15] McArthur, D P, I Thorsen and J Ubøe, 2010,"A Micro-Simulation Approach to Modelling Spatial Unemployment Disparities ", *Growth and Change*, 41, 3, 374-402

[16] McArthur, D P, I Thorsen and J Ubøe, 2014, "Employment, transport infrastructure and rural depopulation: a new spatial equilibrium model ", *Environment and Planning A*, 46 (7), 1652-1665.

[17] McArthur, D P, I Thorsen and J Ubøe, 2020, "Some consequences of ignoring relocations in the cost-benefit analysis of transportation infrastructure investments", in Thill, J-C, Innovations in urban and regional systems: contributions from GIS&T, Spatial analysis and location modeling, Springer, 137-164.

[18] Muth, R F, 1969, "Cities and housing: the spatial pattern of urban residential land use ", Chicago and Londin: The University of Chicago Press.

[19] Page, S E, 1999, "On the emergence of cities", *Journal of Urban Economics*, 45,1, 184-208.

[20] Sen, A and T Smith, 1995, *Gravity Models of Spatial Interaction Behavior*, Springer-Verlag, Berlin and Heidelberg.

[21] Sheppard, E S, 1978, "Theoretical underpinnings of the gravity hypothesis", *Geographical Analysis*, 10, 4, 386-402.

[22] Sheppard, E S, 1984, "The distance-decay gravity model debate."In: Gaile GL, Willmott CJ (eds): *Spatial statistics and models*, Reidel Publishing Company.

[23] Tiefelsdorf, M, 2003, "Misspecifications in interaction model distance decay relations: A spatial structure effect", *Journal of Geographical Systems*, 5, 25-50

[24] Wilson, A, 2010, "Entropy in urban and regional modelling: Retrospect and prospect", *Geographical Analysis*, 42, 364-394.

Predicting induced commuting from a new fixed link in the transportation network.

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Abstract

In this paper, we study to what degree a standard spatial interaction model represents a reliable approach to predicting induced commuting from investments in the road transportation network. The analysis is derived from agent-based data generation, supplemented by observations from a Norwegian labor market area. The results demonstrate that striving for a model specification with the highest possible explanatory power only sometimes leads to the most accurate predictions. Ignoring relevant information on spatial disparities in wages and housing prices and failing to account for relocation effects introduce a potentially serious bias in predicting commuting induced by a new fixed link. The prediction bias depends on the time perspective. The wider local impacts may lead to substantial under-predictions of induced commuting and the willingness-to-pay for a new fixed link. Spatial interaction models should be used with care in particualr in cases where the investments lead to substantial improvements in the labor market accessibility of a previously rural area. In such cases, a cost-benefit assessment should be based on a general spatial equilibrium modeling framework to avoid that induced demand is being under-predicted, calling for expensive capacity expansions of the road network.

JEL-classification: C63, R23, R58,

Keywords: prediction bias, fixed links, commuting, spatial interaction models, agent-based data

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1 Introduction

There is empirical evidence that a standard doubly-constrained gravity model of commuting fails to capture the effect of several characteristics of spatial structure (Thorsen and Gitlesen, 1998). In addition, Gholami et al. (2023b) have demonstrated that local labor and housing market conditions are relevant in explaining the commuting pattern. Hence, spatial interaction models can be extended in different directions to improve the explanation of commuting in a region. This paper will discuss such model extensions in an experimental modeling approach. However, our main ambition is to test to what degree a more advanced model specification contributes to more accurate predictions following an exogenous shock. The exogenous shock to be considered in this paper is related to investments to establish a new fixed link between specific towns in a geography, that is, investments generating a new road or rail connection across a topographical barrier. The predictions can be made for the matrix of commuting flows in general and for the induced commuting on specific road links of the transportation network.

Using a doubly-constrained spatial interaction model specification with omitted relevant information is just one source of a potential prediction error. In addition, it is a potentially severe shortcoming of such a model that both the spatial residential pattern and the location of jobs are assumed to be given, unaffected by, for example, changes in the road transportation network. This can, in particular, be argued to represent a severe shortcoming if the predictions are made for a long-term time perspective. Changes in the road transportation network open new opportunities in the location choices of both firms and households and may, as such, result in relocations that affect the trip distribution pattern. To some degree, moving and commuting is, for example, substitutes in the spatial behavior of households. For example, a new road connection may lead households to move into a more peripheral residential area, contributing to increased urban sprawl, which may cause a longer commuting distance and induce more traffic on the new road connection. In this paper, we will discuss how ignoring relocation effects potentially result in biased predictions of induced traffic and, accordingly, biased predictions of the benefits emerging from investments in road infrastructure.

It seems like a reasonable hypothesis that the relocation effects of changes in the road infrastructure are sluggish. The prediction bias based on a standard spatial interaction model will be more severe in the long term than in the short-run time perspective. In a dynamic system, the location pattern of jobs and households can change continuously. This can be argued to undermine the functioning of a doubly-constrained spatial interaction model as a framework for making reliable predictions on induced travel demand and the benefits of the investments. It further provides arguments in favor of employing a combined transport and land use modeling framework in predicting the effects of substantial changes in the road network.

In this paper, we employ a general spatial equilibrium model to generate data for our experiments. However, this modeling framework is constructed to make a synthetic population in a fictive geography rather than based on real-world data. This approach enables us to study prediction biases resulting from a parsimonious model formulation and from ignoring relocation effects.

Ideally, predicting the induced demand and the benefits of investments in road infrastructure should be based on data on all relevant aspects. However, such a complete data set is, in general, not available. According to Nicolaisen and Driscoll (2014), the lack of data availability for comprehensive ex-post appraisals of demand forecasts accuracy for transport infrastructure projects is the main reason why such studies are rare. Using synthetic data can often be an interesting and acceptable replacement. Microsimulations also represent an appealing alternative to purely analytical approaches. There are limited opportunities for this complex, multidimensional problem to reach a wide range of interesting results based on analytical approaches. Hence, the lack of adequate real-world data and the limitations of analytical approaches are the main reasons we generate data from an agent-based general spatial equilibrium modeling approach. This approach has a vast potential to clarify, explain and predict complex interdependencies between spatial interaction, land use, and labor market issues. Such an experimental design also represents a convenient way to deal with issues related to endogeneity and causality, which are often serious and complex problems to overcome in empirical analysis.

Both the experiments to be run and the discussion to follow is made in terms of a new fixed link introduced into a region's road transportation network. This is, for instance, often discussed in a Norwegian context, where transportation investments are used to overcome the effect of topographical barriers by building bridges or tunnels in areas with fjords and mountains. Still, the effects of new fixed links and transportation investments, in general, are relevant in most geographies. Such investments are customarily assessed by predicting construction costs, increased traffic, and user benefits. According to Nicolaisen and Driscoll (2014), empirical studies of cost estimates are in ample supply, generally indicating a dominating tendency of cost overruns (Siemiatycki, 2009). As mentioned, predicting user benefits in a dynamic perspective is complicated by the likely impact on the location decisions of firms and households and possible policy aspirations related to the impact on local development in rural areas. It has been claimed (Tveter et al., 2017) that Norwegian planners ignore the effects of relocation decisions on the estimated user benefits of the projects.

This paper's primary motivation is to demonstrate how ignoring relocation effects may lead to a severe bias in estimating the user benefits of road investments. Nicolaisen and Driscoll (2014) found a general tendency to underestimate travel demand for road projects in a literature review. They also found a tendency that the bias is more severe for studies of individual road segments than for studies including screening analysis. This indicates that the problem is related to predicting the network distribution rather than the travel demand. In their literature review, Nicolaisen and Driscoll (2014) found that information on the model specification used in travel demand studies is nearly impossible to acquire. They also refer to studies finding that improvements in modeling tools have not led to an improvement in forecast accuracy over time. This indicates that improving the model specification does not represent the main potential for improving the forecast accuracy. Nicolaisen and Driscoll (2014) claim that more detailed access to project data is necessary to analyze causal mechanisms and sources of demand forecast inaccuracy. Our ambition in this paper is to demonstrate that agent-based data generation represents another promising approach to conducting a detailed analysis of such matters.

Section 2 explains relevant concepts and theory and offers a review of relevant literature. The agent-based generation of synthetic data is described in Section 3, while Section 4 discusses alternative model specifications in explaining commuting trips in a region. Section 5 addresses alternative approaches to how a spatial interaction model can predict induced commuting on a new road. The possibility of relocation effects of improvements on the road transportation network is discussed in Section 6, before Section 7 provides estimated results and predictions from employing different specifications of a spatial interaction model to data generated by the agent-based approach. We study another realization of the data-generating procedure in Section 8, and then in Section 9 provide data on real-life experiences of wider local impacts in some cases where new fixed links are introduced in a Norwegian labour market area. Concluding remarks are offered in Section 10.

2 Relocation effects, local growth, and wider economic impacts

It is well known that a cost-benefit appraisal of a new road generally calls for a prediction of induced traffic. Hence, the standard approach to estimating the benefits of changes in the road transportation network is to start by predicting the induced demand for transport. For linear, or close to linear, demand curves, the next step may be to measure transport user benefits by applying the rule of a half; see, for instance, Small and Verhoef, 2007, p. 183. This rule may also work well for small changes in quantity for non-linear demand curves.

In this paper, we are focusing on commuting, representing a trip purpose that is particularly interesting from an urban and regional planning perspective. Commuting is a dominating trip purpose in rush hours, challenging the road capacity and the local traffic flow. We are concerned with the first step, which is estimating the demand curve and the induced demand for commuting. As an alternative approach, Gjestland et al. (2014) demonstrate that the estimation and measurement of the change in the consumer surplus of commuters can be based on the capitalization of the housing market. However, based on a spatial interaction approach, the doubly constrained-gravity model is the benchmark in estimating how changes in the road transportation network affect the commuting pattern and the induced commuting across a specific new road. Our main motivation is to discuss to what degree this doubly-constrained modeling framework needs to provide reliable predictions of induced commuting. One critical issue is that the doubly-constrained framework assumes a fixed location pattern of jobs and workers. This assumption can be argued to be unreasonable, particularly when a new fixed link is introduced into the road transportation network.

2.1 Relocation effects

The theory supports the hypothesis that a new fixed link will influence the location decisions of households and firms. The new road opens for a potentially attractive job and residential location combinations for households. Housing prices, in general, are expected to be lower in rural areas than in more densely populated urban areas. With a considerably reduced commuting distance between the two areas, some urban citizens may move to a lower-priced house in the peripheral region and commute to their job in the urban area. The possibility that a reduced housing price is traded off against higher commuting costs is in line with the primary mechanism in bid-rent theory for the housing market, as discussed in any textbook on urban and regional economics, like Brueckner (2011), McCann (2013) and Capello (2016). Thorsen and Ubøe (2002) discuss residential location choices in areas with topographical barriers. In a purely rural context, they ignore the effect of housing prices and, in a theoretical probability approach, demonstrate how a new road link may affect the utility-maximizing residential location and the net migration from the peripheral area.

Innovations in the transportation infrastructure, like a new fixed link, may also affect the location decisions of firms. As claimed in Weberian location theory, the optimal location of a firm often reflects a trade-off between labor costs and transportation costs. Labor costs reflect a wage gradient falling from the center of geography. On the other hand, transportation costs are more likely an increasing function of the distance from the center, reflecting the access to the sources of inputs and the market for the output. This represents a kind of effect following changes in the transportation infrastructure that has, for instance, been addressed in the literature on spatial general equilibrium models; see Venables (1996) for an early and seminal contribution.

Hence, a new fixed link potentially affects both the utility-maximizing residential location and the cost-minimizing location of firms. In addition, changes in the location pattern of firms and households reflect the interaction between these two groups of agents. This interaction is represented by the economic base multiplier mechanism, where an increased local population attracts local sector firms, offering job opportunities that attract more households, and so on. For a discussion of the interaction between the location decisions of households and local sector firms, see, for instance, Gjestland et al. (2006).

In general, it is important to account for the possibility that purely distributive effects may be involved, which means that positive effects in one region are counteracted by similar negative effects in other regions. However, the relocation of firms and households to be considered in this paper, are intraregional. The new road opens for new options, which potentially involve increased utility for some households, and increased profit for some firms. The basic idea in cost-benefit analysis is that such benefits are measured by the increased willingness to pay for travelling. Our main ambition is to study the suitability of a doubly-constrained modelling framework to predict the induced commuting and the increased willingness to pay resulting from a new road between two towns, in an intraregional perspective.

Figure 1 provides an illustration of the potential prediction bias that follows from ignoring intraregional relocations following from a substantial reduction in travelling costs at a specific link in the road network. The figure is reprinted from McArthur et al. (2020). The general cost of travel across the link is represented at the vertical axis, while the horizontal axis represents the number of trips. The demand curve estimated by the observed trip distribution is given by 'Ex' in the figure. Initially, the generalized cost of travel is P_0. According to the demand curve, this means that the demand for trips will then be T_0, corresponding to a consumer surplus of ABP_0.

Assume next that the investments in the road transportation network lead to a reduction in the generalized cost of travel from P_0 to P_1, inducing an increased number of trips from T_0 to T_1. This leads to an increased consumer surplus given by the area P_0BDP_1 for the users who made the T_0 trips and BCD for the new, induced, users. However, the demand curve 'Ex' is based on the assumption that the location of jobs and workers is fixed. Hence, this does not account for the possibility that a new road adds more flexibility both to residential location choices and to the location of firms. The outcome of increased flexibility of course reflect individual preferences. Still, considerations based on bid-rent theory can be used as arguments in favour of relocations involving more traveling in a case with reduced generalized cost of travel. This is reflected by the demand curve 'En' in Figure 1. Ignoring relocation effects then means that the induced traffic is

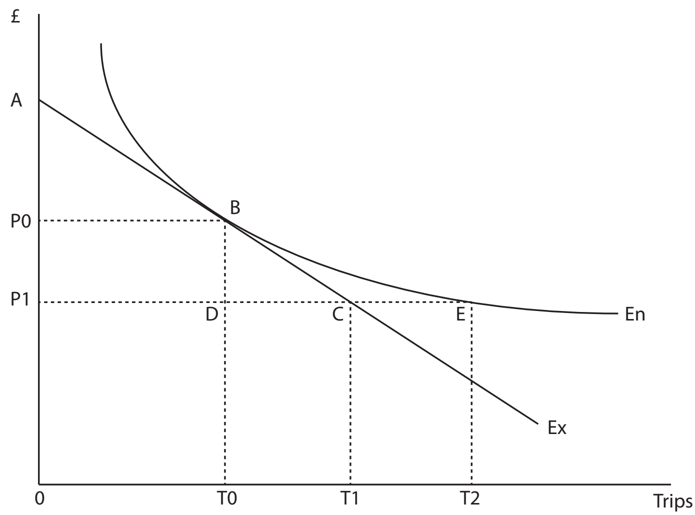

Figure 1: The demand for trips across a specific link, with and without accounting for relocation effects.

underpredicted by $(T_2 - T_1)$, while the induced consumer surplus is underestimated by the area BCE. This is an illustration that it is potentially important to account for the possibility that the agents may take advantage of changes in the road transport network by relocating. Tveter et al. (2017) claim that Norwegian road planners neglect the possible indirect effect of changes in settlement patterns on traffic flows and estimated benefits of a project. One ambition of this paper is to use data from a synthetic population to discuss the magnitude of prediction errors resulting from a model based on the assumption of a fixed location pattern.

2.2 Local growth

From the discussion above it follows that a new fixed link can be expected to influence the local growth of different towns in a region, and this should ideally be accounted for in predictions of induced commuting. The relocation effects represent the basic component of what Welde and Tveter (2022) denotes to be the wider local impacts. Policy ambitions related to wider local impacts contribute to explain and defend why the assessment and ranking of potential transport investments are not necessarily according to a standard cost benefit appraisal of user effects (Gühneman et al., 2012, Eliasson et al., 2015). A dominating concern in policy-making may for instance be to reduce spatial disparities between central and peripheral areas in a region.

Based on data from ten Norwegian road projects, Welde and Tveter (2022) study wider local impacts in terms of four different indicators; commuting, population, new firms, and employment. In this paper, we focus on the likely possibility that there are interactions between these indicators, and that such interactions ideally should be explicitly accounted for in an appraisal of the projects. Welde and Tveter (2022) in general report mixed results of the impact on local development of transport infrastructure investments, and claim that this is in line with most studies. Based on their findings, they further claim that road investments is a potent instrument in providing local growth only in cases where a relatively weak area gets a significantly improved connection to larger labour markets.

In a standard cost-benefit appraisal of a new fixed link, the benefits of individual agents are represented by their aggregate willingness to pay for transport involving the link. In addition, a policy ambition can be attached to the impact of transport investments on the spatial distribution of people and jobs. It can be argued that a more centralized pattern of jobs and people generates less transport in a more sustainable spatial development of a region. However, it can also be argued to benefit the society that the rural settlement pattern is preserved in a more balanced development of central and peripheral areas of the region. Hence, for any specific policy ambition, the impact of a new fixed link on local growth can be attached to a separate value beyond the aggregate of individually measured benefits.

According to, for example, Deng (2013), Crescenzi et al. (2016), Elburz et al. (2017), and Wang et al. (2020), there is a controversy concerning both the direction and magnitude of the growth effects of investments in transport infrastructure. Deng (2013) analyses why the evidence of the growth-enhancing effects is mixed and identifies ten essential factors for the wide range of elasticity estimates in the literature. The general belief seems to be that investments in transport infrastructure represent a crucial facilitator of economic growth (Donaldson, 2018; Saidi et al., 2018), but there are also many studies suggesting that the impact of such investments is insignificant or even negative (Locatelli et al., 2017; Maparu & Mazunder, 2017).

The possibility of a negative impact on local growth is also addressed by Welde and Tveter (2022). They point to the possibility that a new fixed link that improves the accessibility between two areas benefits the prosperous and most vigorous region in terms of growth. In this respect, Welde and Tveter (2022) also address goal conflicts. The ambition to increase or preserve the population in peripheral areas may come at the expense of agglomeration economies and costs related to CO_2 emissions of long-distance commuting and urban sprawl. This conflict is referred to as the two-way road effect. Welde and Tveter (2022) point out that better roads can reinforce existing trends and patterns, exacerbating spatial disparities. Tveter et al. (2017) refer to the two-way road effect as the possibility that road investments lead to centralizing economic activities.

2.3 Wider economic impacts

The wider local impacts may reflect the outcome of a zero-sum game in the sense that they are distributional. Still, they are relevant in assessing different projects since distributional effects matter in an overall evaluation, with the policy ambition of reducing unfortunate disparities between different areas. Laird and Venables (2017) do not explicitly distinguish between the wider local and economic impacts. However, distributional effects should be more generally addressed in discussing the wider economic impacts, which reflect the productivity effects of an improved transportation network.

The location decisions of firms result from a trade-off between benefits and costs. Marshallian agglomeration economies contribute to pulling the optimal location towards clusters of other firms, generating benefits from learning, sharing, and matching (Duranton and Puga (2004) and from risk-sharing in pooled labor markets (Ellison et al., 2007). Agglomeration economies represent positive externalities contributing to increased productivity and local growth. Wangsness et al. (2017) provide a review and a discussion of the possibility that the observed relationship between productivity and agglomeration may come from statistical sorting and selection effects. Graham and Gibson (2019) have estimated how bringing firms and labor markets closer to each other contributes to increasing productivity and welfare in the economy in general. This productivity gain of a spatially more densely concentrated economic activity has as its counterpart an urban wage premium that is well documented in the literature (Melo et al., 2009).

This discussion is related to the wider economic impacts (WEIs) of investments in road infrastructure. Agglomeration economies represent an essential source of indirect effects which are not adequately accounted for in the standard cost-benefit analysis, see for instance, Graham

(2007), Venables (2007), and Henschel et al. (2012), and see Oosterhaven and Knapp (2003) for a distinction between direct and indirect effects of changes in the road network. Wangsness et al. (2017) also provide a discussion of other effects leading to WEIs of transport infrastructure investments. They distinguish between five different labor market effects and discuss impacts in imperfect competition markets. Such effects include the possibility that firms are getting reduced monopsonistic power over workers and the welfare increase caused by the effect of increased competition on product differentiation.

Agglomeration economies are, of course, not the only factor influencing the location decisions of firms. At the same time, firms may prefer to take advantage of lower-priced land and labor, which tend to pull towards more peripheral locations; a new road link may connect a rural area close enough to a regional center to gain from agglomeration economies while at the same time benefit from lower prices of land and labor. A relevant discussion of such trade-offs can be found in the New Economic Geography literature, for instance, Venables (1996).

There is extensive literature on the contribution of transportation infrastructure to productivity and economic growth in general, see Deng (2013) for a review, and Chatman and Noland (2011) for a review focusing on the effect of agglomeration in particular, that is "external economies of scale in density and diversity of firms". Kasraian et al. (2016) studied the long-term impacts of transport infrastructure networks on land use. The long-term perspective makes it more likely to capture the slow land-use development arising from changes in the road transportation network. It makes it possible to study various stages in history. Tveter and Laird (2018) also claim that wider impacts may take a long time to materialize and that they may be spread over a wide geographical area. Kasraian et al. (2016) refer to studies indicating that highways attract commercial or industrial developments while suppressing residential development. Tveter (2020) evaluated several attempts from the Norwegian Public Roads Administration to estimate the potential wider impacts of planned road projects. The estimates were found to variate substantially, from close to 0 to more than 200 percent of user benefits. Tveter (2020) found that the results are susceptible to the chosen model specification.

Some ambiguity can be found in the literature on the practical relevance and importance of wider economic impacts in evaluations of investments in transportation infrastructure. Based on a survey of meta-analyses, Melia (2018) finds that reports on wider economic impacts tend to reflect personal judgments rather than empirically based evidence. On the other hand, Gibbons et al. (2019) provide empirically-based evidence that even exposure to relatively incremental transport improvements results in substantial positive effects on the number of establishments and employment in an area. Using a dataset of 31 UK road construction schemes carried out between 1998 and 2007, they approached the problem by measuring how transport improvements lead to changes in accessibility within targeted areas. Welde and Tveter (2022) claim that wider economic impacts may be unobservable at the local level and that local results may interest policymakers the most.

3 Generation of synthetic data; an agent-based approach

In this section, we provide a very brief presentation of the process of generating data for the experiments to be presented in subsequent sections. Data are generated by an agent-based modeling approach, which corresponds to the case where "the system of interest is populated by individual agents who are given (probabilistic) rules of behaviour"(Wilson, 2010). A technically more detailed explanation of how the population and the regional economy are generated can be found in Gholami et al. (2023). In Gholami et al. (2023), the analysis was based directly on experiments from the agent-based modeling framework, while we in the current paper uses this approach just to generate trip distribution data for model experiments based on spatial interaction models. Hence, a detailed presentation of the agent-based model is more dispensable, and we restrict it to the essential elements of the data-generating process:

The geography is defined by the 12 towns illustrated in Figure 2. A main point of interest in this paper is that a new road connection is being constructed between towns B and E. Town E hosts the central business district of the geography. The distance between these two towns is 60 km prior to the investment of the new bridge, or tunnel, across the topographical barrier, which may be in the form of a fjord, a lake, or a mountain. In the situation after the new road, the distance is 15 km. All the distances in the system are proportional to the length of their respective links in Figure 2.

The demographics. After an initialization where 15000 17-year-old utility maximizing agents are randomly born in specific towns, the population in a base year follows from a 300-year-long interaction process, where the agents are born, get married, divorced, have children, apply for work, are retired, and die, according to rules based on Norwegian statistical data. After this long interaction period, all the initial population traces are wiped out, and we know the state of each agent in terms of gender, age, spouse, parents, children, house, work location, income, wealth, etc. Mortality rates are based on life insurance tables; the chances of marrying a person in another town are assumed to decline exponentially with distance, and birth rates and divorce rates are based on data from the Norwegian population.

The preferences. The individuals are equipped with a utility function based on the assumption that they derive utility from the disposable income for consumption in a lifetime perspective and from housing consumption, represented by the size of the house, measured by the number of squared meters. A parameter is introduced into the utility function, reflecting the elasticity of the utility concerning lifetime disposable income and the size of the house.

Employment. We distinguish between local sector firms and basic sector firms. The first serves the local population, while the latter serves demand in other regions and countries. The basic sector employment in a town is considered exogenous, while the local sector employment depends on the local demand. There are assumed to be three groups of workers and three categories of jobs within the local and basic sectors. Within each group, the workers are assumed to be homogenous regarding labor market qualifications. Each individual is born to belong to a specific occupational group, with probabilities depending on gender and reflecting a specific distribution of the population into different groups. Each of the six industrial sectors is specified to demand given the proportions of the three groups of workers.

Wages and unemployment. For each group of workers, the wage rate is set higher in town E, the CBD, than in the other towns, initially to account for high local productivity due to agglomeration economies. For the following years, wages are determined through a local Phillips curve style mechanism. If unemployment is non-existing and the local demand is high for a category of workers, this will result in high local wages for this group of workers. There are no other sources of income than the wage, but there is an income tax, and unemployed agents receive an insurance payment.

Housing demand. Each year, the agents make a random check to see if they will bid for houses on sale, and house owners decide whether their house joins the pool of houses for sale. All the potential bidders scan the pool of houses for sale in search of the house, providing them with the maximal utility. They join a pool of bidders if the specific house contributes to improving their position. The bidding procedure representing the housing demand uses first-price sealed bid auctions. All bidders submit their bids simultaneously, and the highest bid wins the auction. The seller then considers the winning bid and the sale is carried out if this bid exceeds the seller's reservation price. A house is removed from the pool if a sale is executed.

Housing supply. The regional government planning entity is responsible for the initial supply of housing and also for supplying proportional yearly increases in the housing supply in each town. In addition, the local building frequencies reflect a high local demand, represented by a given elasticity of housing supply with respect to the local price increase observed in the previous year.

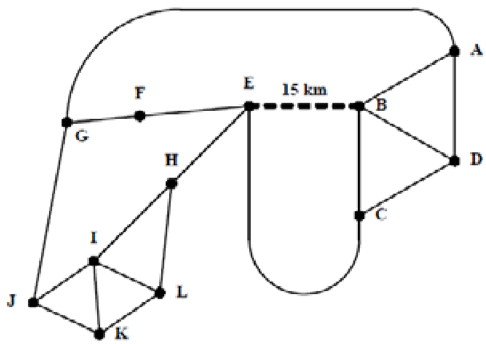

Figure 2: The spatial configuration of zones in the geography.

The agent-based model used for providing trip distribution data for this paper differs from that used by Gholami et al. (2023). The labor market heterogeneity in different categories of jobs and workers represents an extension of the modeling framework. This heterogeneity introduces an additional source of friction into the system that can contribute to explaining some of the commuting between the towns in the system. At the same time, this opens both spatial wage disparities and disparities in unemployment rates for different groups of workers. Other applications of the agent-based approach can be found in for example McArthur et al. (2010, 2012). Compared to the approach used in this paper, the analyses in McArthur et al. (2010, 2012) were, however, based on a set of more restrictive assumptions on the both the geography and the economic mechanisms. The geography was for instance restricted to just two towns, and no housing market was involved.

In this paper, both disparities originating from the labor market and spatial disparities in housing prices affect the migration/commuting trade-off of the households. Assume that a worker is applying for vacant positions and accepts a job offer with higher wages in another town than the current residential location. If the housing prices are higher in the town hosting the new employer, this pulls in the direction of commuting from the current residence rather than migrating to the new job location. If the worker is married, the utility of the spouse is, of course, also relevant in making such a decision. In general, both housing price and wage disparities should be expected to influence the commuting matrix underpinning the spatial interaction analysis in this paper.

After 300 initializing years, a population is designed that, in a demographic sense, represents the Norwegian population. As a next step, the labor and housing markets are integrated into the model, which is then run for another 50 initializing years. The chosen size of the initial population and the housing stock reflects a trade-off between computing time and the demand for achieving robust results for the housing market, the labor market, and the spatial interaction between the 12 towns.

The state reached after 350 years of initialization results from experimenting with values of parameters and exogenous variables. The experiments aimed to create a state with reasonable values of endogenous variables like unemployment rates, housing prices, and wages. They could be observations from a typical Norwegian region. The values of these variables are discussed in Gholami et al. (2023) and are not an issue in this paper. The same applies to the parameterization of the different components of the model that is briefly described above. The parameterization is also described and discussed in Gholami et al. (2023), except that they had no heterogeneity of jobs and workers, as pointed out in the sections about employment and wages above. Concerning the three groups of workers, 20% of the population is assumed to belong to group 1, out of which 80% are women and 20% are men. For group 2, the corresponding figures are 40 % (50%, 50%). At the same time, 40% are also born to belong to group 3, with a distribution of men and women according to an equation ensuring that the system balances gender. Similarly, the distribution of local and basic sector jobs for the overall system is given by 20%, 40%, and 40% for the three categories, respectively. The three sectors can, for instance, be retailing, manufacturing, and the service sector.

It is essential to notice that, just as in real life, the agent-based modeling approach does not reach a steady state equilibrium. It is a complex, dynamic modeling framework where life-cycle considerations and independent individual decisions contribute to continuously changing the system's state. We use the commuting matrix of the first year after 350 years of initialization to estimate spatial interaction models, which are next used for predicting changes in commuting flows. Even with no exogenous changes, the pattern of commuting flows will change, but the system should be expected to be relatively sluggish, with only minor yearly changes. However, this situation changes once the system is exposed to a substantial shock through a new road between towns B and E. We will discuss to what degree a static spatial interaction model can predict the changes in commuting following this kind of exogenous shock.

In a real-world scenario, geography does not only represent a complex, dynamic system; it is also more or less continuously exposed to exogenous shocks. It is a substantial challenge to distinguish the impact of a new fixed link from other exogenous changes in an empirical analysis. In empirical analyses, endogeneity issues related to the interaction between, for example, traffic and the road network or between location decisions and traffic represent a challenge in interpreting the results from a causal point of view. In other words, it is not straightforward to identify what would be local and regional development in an empirical setting if the relevant fixed link was not realized. Both Tveter et al. (2017) and Welde and Tveter (2022) approach this problem by using "the synthetic control method", where the basic idea is to find synthetic control units to imitate the counterfactual development, that is, the development in a case with no new fixed link. For a formal discussion of this approach, see Abadie et al. (2010). In dealing with Norwegian road projects, Tveter et al. (2017) and Welde and Tveter (2022) find control groups of similar municipalities in each case. The similarities are defined, for instance, from the development prior to the new fixed link. It is also a criterion that the municipalities in the control group had no significant changes in infrastructure or other aspects in the period under consideration. The method further makes up composite (synthetic) control municipalities based on data from several similar municipalities. Such an approach is nevertheless subject to an element of uncertainty; as pointed out by Tveter et al. (2017, pp 68), the method "does not provide a definitive test of any causal mechanism". This problem is avoided in our agent-based approach. By employing our experimental design, issues of endogeneity and causality can be easily overcome, and we know exactly what would be the outcome in a scenario without the relevant fixed link.

4 Estimating spatial interaction models

In this section, we will discuss how different specifications of spatial interaction models succeed in explaining the commuting patterns of the synthetic population of workers generated by the agent-based modeling framework. We will see how the results compare to real-life experience with such model specifications, keeping in mind that the results may be sensitive to, for example, spatial structure characteristics, as demonstrated in Gholami et al. (2020). In evaluating the performance of different model specifications, we will use the Standardized Root Mean Square Error (SRMSE):

$$\text{SRMSE} = \frac{\sqrt{\frac{\sum_{ij}(T_{ij}-\hat{T}_{ij})^2}{I \cdot J}}}{\frac{\sum_{ij} T_{ij}}{I \cdot J}}$$

Here, T_{ij} is the number of workers living in town i and working in town j, while I and J denote, respectively, the number of rows (origins) and columns (destinations) in the trip distribution matrix. In the synthetic geography to be considered, $I = J = 12$. The SRMSE was recommended by Knudsen and Fotheringham (1986) as the most accurate measure for comparing model specifications in different spatial systems. In Section 4.1, alternative model specifications are presented before the results based on our synthetic data are presented in Section 4.2

4.1 Alternative specifications of a doubly-constrained spatial interaction model

The standard doubly-constrained gravity model is a well-known and commonly used model for trip distribution problems. In terms of commuting, the basic idea is that the number of trips

- originating from town i relates to the number of workers living here
- destination in a town j is related to the number of jobs located here
- between an origin i and a destination j is negatively related to the distance between the two towns

At the same time, any spatial interaction model should account for the marginal total constraints corresponding to a fixed number of workers and jobs in each town. Let O_i be the number of workers living in town i, while D_j is the number of jobs in town j. The marginal total constraints are then given by $\sum_j T_{ij} = O_i$ and $\sum_i T_{ij} = D_j$, $\forall i, j$. The standard doubly constrained gravity model can be formulated as follows:

$$T_{ij} = A_i O_i B_j D_j \exp(-\beta d_{ij}) \tag{1}$$

$$A_i = \left[\sum_j B_j D_j \exp(-\beta d_{ij}) \right]^{-1} \tag{2}$$

$$B_j = \left[\sum_i A_i O_i \exp(-\beta d_{ij}) \right]^{-1} \tag{3}$$

Here, d_{ij} is the traveling time by car from origin i to destination j, and β is a distance deterrence parameter. At the same time, A_i and B_j are the balancing factors that ensure the fulfillment of the marginal total constraints. This model is rooted in stochastic utility theory (Anas, 1983) and entropy-maximizing and cost-efficiency theoretical approaches (Erlander & Stewart, 1990; Sen & Smith, 1995).

Intuitively, this model seems parsimonious, with relevant characteristics of spatial structure omitted. However, the balancing factors account for the effect of many characteristics relating an origin i to a specific destination j. Attempts to incorporate such variables into the model may affect the estimated values of the balancing factors. In contrast, the estimates of the structural parameters and the goodness of fit will be unaffected. Still, the literature offers evidence that some variables representing the spatial characteristics affect the parameter estimates and the model performance. Below is a list of model extensions to be tested by our synthetic data. The presentation focuses on the changes made in the structural equation. Remember that the balancing factors, of course, must be revised correspondingly.

The competing destinations model adds a measure of labor market accessibility to the model. This approach was originally suggested by Fotheringham (1983, 1986), primarily for other forms of spatial interaction than commuting. However, the accessibility measure has been proven to contribute significantly to explaining commuting flows in a competing destinations model formulation; see for instance, Thorsen and Gitlesen (1998) and Gitlesen and Thorsen (2000) for both results and interpretations. With such a model formulation, the structural part is formulated by

$$T_{ij} = A_i O_i B_j D_j S_{ij}^{\rho} e^{-\beta d_{ij}} \tag{4}$$

If the agglomeration kind of force is dominant, the sign of ρ will be positive, while the parameter takes on a negative value if the competition kind of force dominates. The accessibility of destination j relative to all the other destinations, S_{ij} as perceived from i is defined by:

$$S_{ij} = \sum_{\substack{k=1 \\ k\neq i, k\neq j}}^{w} D_k e^{-\beta d_{jk}} \tag{5}$$

where w is the number of potential destinations.

Benefits of residing and working in the same zone can be accounted for by a parameter attached to the Kronecker delta. For instance, the potential benefits are discussed by Thorsen and Gitlesen (1998), who also introduce measurement errors related to intrazonal commuting as a rationale for this model formulation. They conclude that accounting explicitly for the diagonal elements of the commuting matrix adds significantly to the explanatory power:

$$T_{ij} = A_i O_i B_j D_j e^{(-\beta d_{ij} + \mu \delta_{ij})} \tag{6}$$

Here, δ_{ij} is the Kronecker delta,

$$\delta_{ij} \begin{cases} 0 & \text{if } \ i \neq j \\ 1 & \text{if } \ i = j \end{cases}$$

while μ is a start-up cost to be incurred if work and residence are not in the same zone.

Local labor market information can be represented by the demand for labor originating from the firms in a zone relative to the supply of labor originating from the local households. This reflects the prospects of receiving job offers locally and may account, for instance, for different benefits of residing and working in the same zone, as well as the tendency that local firms that possess monopsonistic labor market power in employing local workers see Thorsen and Gitlesen (1998). The local labor market situation can be accounted for as follows:

$$T_{ij} = A_i O_i B_j D_j \left(\left(\frac{O_i}{D_j} \right)^{\alpha_1} \right)^{\delta_{ij}} e^{(-\beta d_{ij} + \mu \delta_{ij})} \tag{7}$$

The hypothesis is that a high value of O_i relative to D_i results in a high T_{ii}, with local workers occupying local jobs. The hypothesis corresponds to parameter values of $\alpha_1 > 0$, which is supported by Thorsen and Gitlesen (1998) results.

The local levels of wage and housing prices. This model modification is motivated by the results of Gholami et al. (2023b), where the estimated distance deterrence parameter was demonstrated to depend on disparities in wages and housing prices across the towns in the geography. The following model formulation accounts for the local variations of wages and housing prices:

$$T_{ij} = A_i O_i B_j D_j \left(\left(\frac{W_i}{H_j} \right)^{\alpha_2} \right)^{\delta_{ij}} e^{(-\beta d_{ij} + \mu \delta_{ij})} \tag{8}$$

A high local wage attracts job applicants from other towns. Hence, many local jobs can be expected to be occupied by workers from other towns. This causes high in and out-commuting to and from the town. A low local level of housing prices contributes to attracting households to reside here. For a given spatial distribution of jobs, this contributes to an increase in the number of out-commuters from the town. All in all, this corresponds to a hypothesis of $\alpha_2 > 0$.

The experiments reported by Gholami et al. (2023) demonstrated that several system-wide characteristics affect the level of labor market interaction between the towns and, thereby, the distance deterrence parameter estimates. This applies, for instance, to the system's compactness, centralization, clustering of jobs, unemployment insurance, commuting costs, etc. Such sources influencing the total commuting are not straightforward to account for in a model using a single cross-sectional data set, with no variation in the relevant variables. The balancing factors in a standard doubly-constrained gravity model will also capture many relevant aspects of the spatial structure. Utilizing the time-series data from our agent-based experiments opens for many interesting analyses in this direction, for instance, by studying how changes in wages, housing prices, or some of the variables mentioned above affect commuting decisions and the estimates of the distance deterrence parameter. However, this is beyond the scope of this paper and will not be elaborated further here.

4.2 Results based on different model specifications

It is well known in econometrics that omitting relevant explanatory variables from a model specification potentially causes biased parameter estimates and poor goodness of fit. In this section, we will discuss how much can be gained from including spatial structure characteristics and variables representing the housing and labor market situation. We will, in particular, see how the model performance benefits from using local data on wages and housing prices, which are not, in general, readily available in real-life scenarios. The model's specifications to be considered are:

M1 The standard doubly-constrained gravity model; Equations (1).

M2 The competing destinations model; Equation (4).

M3 A model accounting for benefits of residing and working in the same town; Equation (6).

M4 A model accounting for the local demand relative to the local supply for labour; Equation (7).

M5 A model accounting for local wages relative to housing prices; Equation (8).

M6 A synthesis of M3, M4 and M5.

The estimation results from these spatial labor market interaction specifications are given in Table 1. The standard deviations are estimated by bootstrapping.

As mentioned above, Thorsen and Gitlesen (1998) found that the competing destinations hypothesis, represented by model specification M2 above, is also relevant for journeys-to-work.

Table 1: Results on different model specifications.

	M1	M2	M3	M4	M5	M6
β	0.049273	0.048088	0.0360717	0.037168	0.0361169	0.0360352
	(0.0011)	(0.0013)	(0.00086)	(0.00087)	(0.00073)	(0.00073)
ρ		0.062				
		(0.0412)				
μ			0.372418	0.40526	-0.74482	-0.83104
			(0.0259)	(0.0228)	(0.0204)	(0.0229)
α_1				0.463625		-0.0370424
				(0.0630)		(0.0623)
α_2					0.655498	0.704493
					(0.0115)	(0.0123)
SRMSE	0.248529	0.247613	0.202552	0.162352	0.158972	0.158954

Note: standard deviations in parentheses.

Based on data from western Norway, they found that competition forces dominate. This contradicts the hypothesis that the increased opportunity to combine the journey-to-work with other activities dominates choosing a preferred job location. Competition effects may reflect congestion for commuting trips into an area with a concentrated cluster of job options. The model specifications M3 and M4 both relate to within-zone conditions. According to Thorsen and Gitlesen (1998), the hypotheses that $\mu > 0$, $\alpha_1 > 0$, and $\alpha_2 > 0$ can be explained, for example, by the advantages of running a two-worker household and a local labor market situation giving rise to monopsonistic wage setting. Data from western Norway supported these hypotheses; see Thorsen and Gitlesen (1998).

The rationale for the hypotheses underlying M2, M3, and M4 sounds reasonable in a real-life scenario. However, our agent-based scenario needs to account for the potential advantages of multipurpose trips. There are neither traffic congestion issues, advantages of running a two-worker household, nor the possible influence of market power in the local labor market. Hence, none of these reasonable hypotheses contribute to explaining the estimated results in Table 1. This opens alternative explanations based on the mechanisms incorporated in our agent-based approach.

One reasonable explanation is related to the ambition of minimizing commuting costs for the household, ceteris paribus. Since many households have two workers, this may pull both in the direction of living and working close to a cluster of alternative job opportunities with high labor market accessibility and in favor of accepting job offers from firms in their hometown. Hence, the hypotheses representing M2, M3, and M4 can be given a probabilistic interpretation related to the likelihood that specific residence and job locations involve low commuting costs for the household. In addition, measurement errors are potentially relevant, for instance, because intrazonal distances are ignored (Thorsen & Gitlesen, 1998).

The results in Table 1 demonstrate that model performance improves considerably, particularly when labor and housing market conditions are incorporated in the model specification. The volume of commuting trips is positively related to the level of local wages relative to housing prices. These results are reasonable. The agents in our data-generating process are utility-maximizing, preferring high wages and low housing prices. In interpreting the results based on the model specification M6, however, the diagonal elements of the trip distribution matrix are represented by several elements. In this case, the individual parameter estimates should be interpreted with care, since they should be expected to reflect covariation of the variables defined for the diagonal elements.

The most prominent result reported in Table 1 is that the different modifications improve model performance compared to the standard doubly-constrained gravity model, an SRMSE of 0.16 represents a considerably better fit than a value of 0.25. One interesting question is to what degree this contributes to more reliable predictions of induced commuting, for example, as a response to a new bridge between towns B and E.

5 Different approaches in providing predictions of induced commuting.

The chosen approach for providing predictions of induced commuting, of course, depends on the resources and the time available. Still, different approaches exist to using a spatial interaction model in predicting induced commuting. For a large-scale project, a spatial general equilibrium approach may be chosen, for instance, to capture the interdependency between location, land use, and transport of changes in the transport network. A smaller, less resource-intensive approach uses a spatial interaction model without a separate module to account for possible changes in the location pattern of jobs and households. In this paper, we do not consider the wider impacts and changes in the land use of investments in road infrastructure.

5.1 The naive approach

In a linear regression model, predictions are typically made by inserting new values of the independent, exogenous variables into the fitted regression model. Consider the model specification M1, where β is the only structural parameter being involved. In fitting this standard doubly-constrained gravity model to data, an estimate of β is reached. Assume next that the matrix of distances was $[d^0]_{ij}$ before the investments in the road infrastructure and $[d^1]_{ij}$ after the investments. In predicting commuting, a straightforward analogy to the linear regression model approach would be to insert the estimated $\hat{\beta}$ and the given values of O_i and D_j into the structural equation (1), ignoring the values of the balancing factors A_i and B_j;

$$T_{ij}^{\text{predicted,naive}} = \hat{O}_i \hat{D}_j \exp(-\hat{\beta} d_{ij}^1)$$

This approach is denoted "naive"since it ignores the balancing constraints. It would be a pure coincidence if the matrix $[T^{\text{predicted,naive}}]_{ij}$ is in correspondence with the balancing constraints $\sum_j T_{ij} = \hat{O}_i$ and $\sum_i T_{ij} = \hat{D}_j$. Despite being naive, this approach may come into use, for example, if data is not available on the trip distribution matrix required to estimate the model's parameters. In contrast, the marginal sums of the matrix are known. Predictions can then be made by us using $\hat{O}_i$ and $\hat{D}_j$, combined with new distances and estimates of the distance deterrence parameter from a previous point in time or from other regions.

5.2 The balanced approach

The investments in road infrastructure provide a substantially shorter distance between the towns B and E in Figure 2. Assume that someone asks for a prediction of induced commuting between these two towns, for instance, due to congestion concerns. The naive approach may impulsively appear reasonable for such an ambition. However, a cost-benefit analysis focuses on induced traffic for the geography in general. In such a perspective, it becomes more apparent why the approach is naive and should not be recommended for any predictions. Still, we keep presenting the naive predictions since they contribute useful insight into the effect of the balancing factors.

The investments in the road transportation network do not affect the distance between all combinations of towns in the system. The distances are not changed for any combination of towns within the clusters of towns that are separated by the topographical barrier; the distances are, for instance, unaffected for any combination of the towns A, B, C, and D. It follows from the equation of $T_{ij}^{\text{predicted, naive}}$ that the naive approach predicts no changes in commuting for combinations of towns where distances are unaffected by the new road. Notice also that the new road is not predicted to lead to fewer commuters between any of the towns in the geography. The situation is very different for the balanced approach.

The balanced approach does not ignore the balancing factors:

$$T_{ij}^{\text{predicted, balanced}} = A_i^1 \hat{O}_i B_j^1 \hat{D}_j \exp(-\hat{\beta} d_{ij}^1)$$

This prediction is based on a recalculation of the balancing factors. A_i^1 and B_j^1 are introduced to ensure the fulfillment of the marginal total constraints $\sum_j T_{ij} = O_i$ and $\sum_i T_{ij} = D_j$ in the case where distances are given by $[d^1]_{ij}$, that is after the investments in the road network.

This means that the predictions are made in an optimization context for a given location pattern of jobs and households and a given estimate of the distance deterrence parameter, $\hat{\beta}$. In such an approach, the commuting flows are, in principle, affected for any combination of towns as a result of the new road between towns B and E. Assume that the new road induces a massive increase in the commuting between towns B and E. Through the impact on the re-estimated balancing constraints, this contributes to reduce the labor market interaction between these two towns and the remaining towns in the geography. The increased commuting between towns B and E reflects the new labor market opportunities due to the new road, explained, for example, by disparities in wages and housing prices. This corresponds to a competition effect in the labor market, for example, making commuting from town B to towns A, C, and D relatively less attractive. It is, of course, a relevant question to what degree the balanced approach accounts for these complex competition effects.

6 Relocation effects of improvements in the road transportation network.

The new road between towns B and E may impact the location decisions of households and firms. As mentioned in Section 2, bid-rent theory suggests that some urban households may reconsider their residential location choice. With a considerably reduced commuting distance between the two towns, some town E citizens may move to a lower-priced house in town B or other towns in the peripheral area on the other side of the topographical barrier and commute to their job in town E.

In addition to production costs and the prospects of agglomeration economies, the location decisions of firms, of course, also reflect their potential sales at alternative locations. For local sector firms, sales depend on the residential location pattern, reflecting that distance affects local customers' shopping decisions. In addition, care should be taken to the possibility of economies of scale and scope in shopping. This explains why retail sales are typically very high in a regional center, calculated per inhabitant. At locations very close to the regional center, the density of local sector firms can be expected to be very low since the local customers tend to benefit from lower prices and multipurpose trips by shopping in the CBD. As the distance increases from the regional center, more households tend to shop locally, as the costs of traveling to the CBD increase. Eventually, the local sector density approaches the regional average for increasing distances to the CBD. Gjestland et al. (2006) provide a theoretical and empirical demonstration of the relationship between the local sector density and the distance from the CBD. Such a relationship is incorporated in the agent-based modeling approach that provides data for this paper as an alternative to the more naive approach that local sector density is proportional to the local population.

The spatial competition, like in the famous Hotelling model, has an additional impact on firms' location choices. The spatial competition for market shares pulls firms towards the market center. However, to soften price competition, firms may want to differentiate or locate at some distance from the market center. This, of course, influences the shopping decisions of households and contributes to modifying the local sector density pattern suggested by Gjestland et al. (2006), but the basic idea remains.

The plausible hypotheses that clusters of households attract firms while a short distance attracts workers to employers bring about an interdependency between these agents. This corresponds to the principle idea in Hoyt's model, making room for the economic base multiplier mechanism in an explanation of local development.

Apart from the spatial competition aspect, the mechanisms mentioned in this section are incorporated in the agent-based modeling approach briefly explained in Section 3. Based on the new road between the towns B and E, bid-rent theory suggests that some households may choose to move out of the CBD to benefit from lower housing prices in the region on the other side of the topographical barrier, at the cost of higher commuting cost to their employment in the CBD. A reduced population may further induce local sector firms to move out, in a process predicting reduced population and employment in the regional center, town E. However, the reduced demand stemming from a reduced local population may be counteracted by the possibility that the households living in towns A, B, C, and D do more shopping in the CBD due to the new bridge. The net outcome of these forces is an empirical question. Figure 3 illustrates the changes in the development of the regional proportions of employment and population in the CBD over 15 years after the new fixed link was constructed between town B and town E in Year 0.

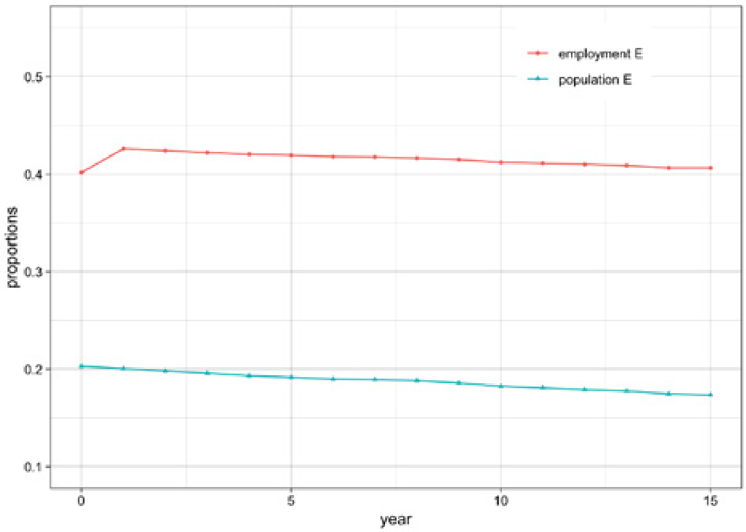

Figure 3: The proportions of the regional population living in the CBD, and the proportion the workers with a job in the CBD, that is town E, in the years after the new link was established between the towns B abd E.

At first sight, the curves in Figure 3 do not represent dramatic changes following from the new fixed link between the two regions at either side of the topographical barrier. Changes in location decisions of firms and households may be relatively sluggish, and the spatial distribution of basic sector jobs is a stabilizing element, as it is assumed to be unaffected by the changes in road infrastructure. However, a closer look at the figure shows that the location effects are substantial according to a priori reasonable hypotheses. The most immediate effect of the new fixed link is to increase the number of local sector jobs in the CBD. This reflects the tendency that more people in, for example, town B will now do their shopping in the CBD rather than locally. This effect dominates the effect of the tendency that people to move from the CBD to benefit from lower housing prices elsewhere in the geography. However, the local sector employment in the CBD will eventually be reduced as the population, and the number of local customers is reduced. The regional proportion of people living in the CBD falls from 0,203 in Year 0 to 0,174 in Year 15. The figures of our agent-based experiments show that this represents a 17,5% reduced population over 15 years. Hence, the location effects following a large-scale change in the road transportation network are substantial in the case we consider.

As mentioned above, the net outcome of different forces affecting the location decisions of firms and households is an empirical question. In studying ten Norwegian road projects, Welde and Tveter (2022) found that some projects resulted in both new firms and increased employment in existing firms, while there is a tendency for negative impacts for other projects. The population growth is not significant for projects in rural areas. However, Welde and Tveter (2022) report substantial effects, particularly for smaller municipalities linked to a city or a regional center, reflecting a process of urban sprawl. They also report a tendency for location effects of firms to build up slowly and may appear many years after the project's opening. Tveter et al. (2017) report considerable lags in the effects on population growth. In general, they find considerable variation in the effect of new fixed links on settlement patterns for the eleven projects they consider. The effects are estimated to be between 10 and 30 percent of population growth for some municipalities and insignificant, or even negative, for others.

7 Predicting commuting flows for a synthetic population

An important application of a spatial interaction model is to make out-of-sample predictions, for example, of how traffic responds to changes in the road transportation network. The predictions are sensitive to, for example, the value of the distance deterrence parameter, which depends on the model specification. In addition, the choice of variables for the model specification can, of course, be expected to affect the predictions, as is the choice of accounting for the balancing constraints or not. In this section, we present results related to prediction issues:

- We first offer predictions for the situation in the benchmark scenario, in year 0, comparing the observed commuting matrix to predictions made by both the naive and the balanced approach.

- As a next step, we present predictions for the situation immediately after a new road is constructed, connecting two clusters of towns located at separate sides of a topographical barrier. The predictions are made for different model specifications and different prediction approaches, comparing both the commuting pattern in general and the induced commuting on the new fixed link.

- Finally, the time perspective is introduced. Predictions are provided for 15 years after a new fixed link is constructed across the topographical barrier. We first discuss how the predictability depends on how the balancing constraints are accounted for, that is, by comparing the naive and the balanced approach that was discussed in Section 5. We also discuss the performance of different model specifications by comparing predicted commuting matrices in general and predicted induced commuting across the new fixed link.

7.1 Predicting commuting flows in the benchmark situation; year 0

First, we will demonstrate how a spatial interaction model predicts commuting flows for the final year in the initializing 350-year-long period, which is also the benchmark, year 0, for experiments in the agent-based modeling framework. Consider first the standard doubly-constrained gravity model, M1. The observed commuting matrix of year 0 is given by T_{ij}^{observed} below, while M1 predicts commuting flows corresponding to the matrix $T_{ij}^{\text{predicted}}$. There is a clear visual resemblance between the two matrices. This is represented by an SRMSE of 0.2485, which corresponds to a reasonably good fit.

Still, there are some discrepancies and room for improvement. It follows from Figure 2 that the geography has two clusters of towns, separated by the topographical barrier. The towns A, B, C, and D are located on one side of the barrier, while the cbd E and the towns F, G, H, I, J, K, and L are on the other. As an example of discrepancies between T_{ij}^{observed} and $T_{ij}^{\text{predicted}}$, M1 considerably under-predicts the number of commuters between the two clusters of towns, located at either side of the topographical barrier. M1 predicts there will be 1415 commuters between the two clusters, while the actual number is 2031. It follows from Table 2 that model extensions accounting for the potential effect of within-zone conditions contribute to predicting more accurately the number of commuters between the two clusters of towns.

$$T_{ij}^{\text{observed}} = \begin{array}{cc} & \begin{array}{cccccccccccc} A & B & C & D & E & F & G & H & I & J & K & L \end{array} \\ \begin{array}{c} A \\ B \\ C \\ D \\ E \\ F \\ G \\ H \\ I \\ J \\ K \\ L \end{array} & \begin{bmatrix} 476 & 177 & 105 & 104 & 180 & 17 & 44 & 18 & 11 & 19 & 9 & 10 \\ 198 & 406 & 117 & 95 & 270 & 40 & 27 & 35 & 17 & 17 & 12 & 17 \\ 98 & 149 & 370 & 51 & 346 & 38 & 35 & 27 & 23 & 18 & 18 & 14 \\ 178 & 137 & 132 & 277 & 219 & 20 & 27 & 19 & 18 & 15 & 18 & 5 \\ 45 & 23 & 50 & 39 & 2112 & 182 & 130 & 175 & 84 & 88 & 72 & 78 \\ 17 & 11 & 17 & 13 & 737 & 261 & 83 & 48 & 23 & 25 & 22 & 20 \\ 18 & 5 & 13 & 13 & 456 & 74 & 369 & 25 & 22 & 59 & 34 & 16 \\ 10 & 9 & 15 & 11 & 611 & 47 & 42 & 262 & 32 & 43 & 57 & 41 \\ 9 & 2 & 7 & 6 & 292 & 32 & 34 & 79 & 164 & 104 & 96 & 48 \\ 13 & 4 & 5 & 16 & 244 & 33 & 42 & 73 & 73 & 303 & 111 & 43 \\ 8 & 0 & 8 & 8 & 227 & 26 & 34 & 60 & 61 & 114 & 340 & 84 \\ 10 & 3 & 9 & 11 & 336 & 23 & 21 & 80 & 65 & 62 & 96 & 186 \end{bmatrix} \end{array}$$

$$T_{ij}^{\text{predicted}} = \begin{array}{cc} & \begin{array}{cccccccccccc} A & B & C & D & E & F & G & H & I & J & K & L \end{array} \\ \begin{array}{c} A \\ B \\ C \\ D \\ E \\ F \\ G \\ H \\ I \\ J \\ K \\ L \end{array} & \begin{bmatrix} 527 & 200 & 100 & 142 & 113 & 14 & 38 & 11 & 4 & 10 & 6 & 4 \\ 232 & 387 & 193 & 131 & 218 & 21 & 17 & 22 & 7 & 7 & 7 & 7 \\ 90 & 149 & 328 & 106 & 369 & 36 & 22 & 37 & 12 & 12 & 12 & 12 \\ 208 & 165 & 173 & 246 & 195 & 19 & 15 & 20 & 6 & 6 & 6 & 7 \\ 6 & 10 & 23 & 7 & 2179 & 212 & 131 & 219 & 72 & 72 & 72 & 73 \\ 3 & 4 & 8 & 3 & 757 & 198 & 122 & 76 & 25 & 32 & 25 & 25 \\ 7 & 3 & 5 & 2 & 439 & 115 & 310 & 44 & 30 & 81 & 50 & 19 \\ 2 & 3 & 7 & 2 & 654 & 64 & 39 & 176 & 58 & 58 & 58 & 59 \\ 1 & 1 & 3 & 1 & 299 & 29 & 38 & 80 & 116 & 115 & 117 & 72 \\ 2 & 1 & 2 & 1 & 236 & 29 & 80 & 64 & 92 & 245 & 151 & 57 \\ 1 & 1 & 3 & 1 & 239 & 23 & 49 & 64 & 93 & 151 & 250 & 95 \\ 1 & 2 & 3 & 1 & 331 & 32 & 26 & 89 & 78 & 78 & 129 & 131 \end{bmatrix} \end{array}$$

With no changes in the road transportation network, there is no reason to distinguish between the naive and the balanced approach to making predictions. The distances are the same over time, the number of jobs and workers (O_i and D_j) are assumed to be constant, and the estimates of parameters are, of course, independent of the choice of prediction approach. The balancing factors will also be estimated to be equal, and the number of commuters across the two clusters will be constant and equal for the two prediction approaches. The values of SRMSE will also be equal for the two approaches, but they will not be constant over time. The reason for this is, of course, that the actual commuting matrix changes over time. The accuracy of the predictions deteriorates over time. Table 2 shows that the SRMSE is 0.2485 for M1. Fifteen years later, the value of SRMSE is 0.6500 for the predictions based on this model. The development of the values of the SRMSE is similar for the other model specifications.

While the predicted commuting matrix remains constant, the commuting matrix following the data-generating process changes continuously. The agent-based modeling framework represents a complex, dynamic system, with relocations causing changes in the marginal totals of the commuting matrix. In this case, the labor market heterogeneities are causing increasing challenges in the matching mechanisms. As a result, long-distance commuting is increasing over time. In year 15, there is an aggregate commuting of 2486 workers across the topographical barrier, while it was 2031 in year 0. This may be a part of a trend around year 0 and is not captured by the spatial interaction models evaluated in this paper. Such trends also represent a potential challenge in real-world scenarios, contributing to poorer fit over time if the model needs to be adjusted to account for new information.

Table 2: The observed and predicted number of commuters across the topographical barrier, in year 0.

	M1	M2	M3	M4	M5	M6
Observed	2031	2031	2031	2031	2031	2031
Predicted	1415	1461	1771	1707	1752	1755

7.2 The standard doubly-constrained gravity model as a tool to predict instant effects of road investments

Consider the case where a new bridge or tunnel connects zones B and E. In a cost-benefit analysis of such an investment in transportation infrastructure, one key element is to estimate the willingness to pay for the new road connection. The estimate of the willingness to pay for the investments reflects the predictions of induced traffic, which further relies on the chosen spatial interaction model specification and the corresponding parameter estimates. As reported in Table 2, the standard doubly-constrained gravity model predicts 1415 commuters between the two clusters of towns, while the actual number was 2031 in the situation before a new road was connecting the towns B and E. From our agent-based data-generating approach, we further know that there will be 2279 commuters across the new road in year 1. Hence, the new road immediately induces 248 commuters across the topographical barrier. How accurate is this induced commuting predicted by the alternative prediction approaches and model specifications?

The new fixed link, of course, leads to a change in the distances, but there will not be any other exogenous changes in the doubly-constrained spatial interaction models considered in this paper. Both O_i and D_j, the parameter estimates and the balancing factors are kept constant in a naive prediction approach. However, in a balanced approach, the balancing factors are adjusted to ensure the fulfillment of the marginal total constraints. Hence, the predictions based on these two approaches differ, albeit separately constant, over the 15-year-long period under consideration.

Consider first the standard doubly-constrained gravity model, M1. Based on this model specification, the commuting matrices $T_{ij}^{\text{predicted, year 1, naive}}$ and $T_{ij}^{\text{predicted, year 1, balanced}}$ demonstrate that the two approaches predict substantially different commuting matrices. They both predict the situation immediately after constructing the new road between towns B and E. By comparing to the predicted matrix for year 0, $T_{ij}^{\text{predicted}}$, notice that the naive approach predicts changes in the number of commuters only for combinations of towns where the distances are directly affected by the new road, and that this approach does not predict a reduced number of commuters between any of the towns in the geography. However, the naive approach predicts an extensively increased number of commuters between the two clusters of towns on either side of the new road. This explains an inferior fit between the predicted matrix of commuters and the observed matrix for year 1, with an SRMSE of approximately 1.58.

The balanced approach performs considerably better in predicting the commuting matrix after constructing the new road. Compared to the observed commuting matrix, $T_{ij}^{\text{predicted, year 1, balanced}}$ has an SRMSE of approximately 0.42. This involves marked discrepancies with the observed commuting pattern and poorer fit than in Year 0, in Section 7.1. Still, the balanced approach, at least to some degree, avoids the extensive over-prediction of commuting between the two clusters of towns following the naive approach. Based on M1, the naive approach predicts that there will be 7042 commuters across the new road immediately after the road's opening, while the correspondent prediction from the balanced approach is 3182 commuters. Based on the prediction that there will be 1415 commuters in year 0, the naive approach predicts that the new road will induce an increase of 5627 commuters, while the balanced approach predicts 1767 new commuters across the topographical barrier. As mentioned above, it follows from our agent-based, data-generating procedure that the instant effect of the new road is just an increase of 248 commuters between the two clusters of towns. Before we elaborate on possible reasons for the poor predictions, we will consider the time perspective of induced commuting and include predictions based on the other model specifications than M1.

$$T_{ij}^{\text{predicted, year 1, naive}} = \begin{array}{cc} & \begin{array}{cccccccccccc} A & B & C & D & E & F & G & H & I & J & K & L \end{array} \\ \begin{array}{c} A \\ B \\ C \\ D \\ E \\ F \\ G \\ H \\ I \\ J \\ K \\ L \end{array} & \begin{bmatrix} 527 & 200 & 100 & 142 & 1036 & 101 & 62 & 104 & 34 & 34 & 34 & 35 \\ 232 & 387 & 193 & 131 & 2003 & 195 & 121 & 201 & 66 & 66 & 66 & 67 \\ 90 & 149 & 328 & 106 & 774 & 75 & 47 & 78 & 26 & 25 & 26 & 26 \\ 208 & 165 & 173 & 246 & 854 & 83 & 51 & 86 & 28 & 28 & 28 & 29 \\ 58 & 96 & 48 & 33 & 2179 & 212 & 131 & 219 & 72 & 72 & 72 & 73 \\ 20 & 33 & 17 & 11 & 757 & 198 & 122 & 76 & 25 & 32 & 25 & 25 \\ 12 & 19 & 10 & 7 & 439 & 115 & 310 & 44 & 30 & 81 & 50 & 19 \\ 17 & 29 & 14 & 10 & 654 & 64 & 39 & 176 & 58 & 58 & 58 & 59 \\ 8 & 13 & 7 & 4 & 299 & 29 & 38 & 80 & 116 & 115 & 117 & 72 \\ 6 & 10 & 5 & 4 & 236 & 29 & 80 & 64 & 92 & 245 & 151 & 57 \\ 6 & 11 & 5 & 4 & 239 & 23 & 49 & 64 & 93 & 151 & 250 & 95 \\ 9 & 15 & 7 & 5 & 331 & 32 & 26 & 89 & 78 & 78 & 129 & 131 \end{bmatrix} \end{array}$$

$$T_{ij}^{\text{predicted, year 1, balanced}} = \begin{array}{cc} & \begin{array}{cccccccccccc} A & B & C & D & E & F & G & H & I & J & K & L \end{array} \\ \begin{array}{c} A \\ B \\ C \\ D \\ E \\ F \\ G \\ H \\ I \\ J \\ K \\ L \end{array} & \begin{bmatrix} 396 & 122 & 69 & 104 & 338 & 34 & 23 & 35 & 12 & 12 & 12 & 12 \\ 139 & 189 & 107 & 77 & 522 & 53 & 35 & 54 & 19 & 19 & 19 & 19 \\ 97 & 132 & 328 & 112 & 365 & 37 & 25 & 38 & 13 & 13 & 13 & 13 \\ 175 & 113 & 134 & 201 & 312 & 32 & 21 & 33 & 11 & 11 & 11 & 11 \\ 114 & 155 & 88 & 63 & 1877 & 190 & 126 & 195 & 67 & 68 & 68 & 68 \\ 40 & 54 & 31 & 22 & 661 & 179 & 119 & 69 & 23 & 30 & 24 & 24 \\ 24 & 32 & 18 & 13 & 389 & 105 & 308 & 41 & 29 & 79 & 48 & 18 \\ 35 & 47 & 27 & 19 & 574 & 58 & 39 & 160 & 55 & 55 & 56 & 56 \\ 16 & 22 & 12 & 9 & 267 & 27 & 38 & 74 & 111 & 113 & 114 & 69 \\ 13 & 18 & 10 & 7 & 213 & 27 & 80 & 59 & 89 & 241 & 148 & 55 \\ 13 & 18 & 10 & 7 & 215 & 22 & 50 & 60 & 90 & 149 & 245 & 91 \\ 18 & 24 & 14 & 10 & 295 & 30 & 25 & 82 & 75 & 76 & 126 & 125 \end{bmatrix} \end{array}$$

7.3 The time perspective in predicting induced commuting from different spatial interaction models.

In a scenario where the distances have changed due to investments in the road transport network, we have seen that predictions of instantly induced commuting depend heavily on whether a naive or a balanced approach is employed. Based on M1, the naive approach predicts that the induced commuting will be more than double the increase predicted by the balanced approach in a short time perspective. This vast difference is crucial in a cost-benefit analysis. However, it is, of course, a legitimate question to ask to what degree this difference depends on the time perspective of the analysis, as well as on the possibility that the spatial interaction model is extended to account for aspects of the spatial structure and spatial disparities in the labor and housing market conditions.

7.3.1 Predicting the regional commuting pattern

Before we return to the number of commuters across the former barrier in the road transportation network, we will consider the predictability of different model specifications for the commuting pattern in general. The agent-based data-generating modeling framework equips us with the "observed" commuting matrix for the 15 years after the opening of the new road. Hence, the predictions following different model specifications and prediction approaches can be evaluated against the observed commuting pattern for each year, measured by the SRMSE.

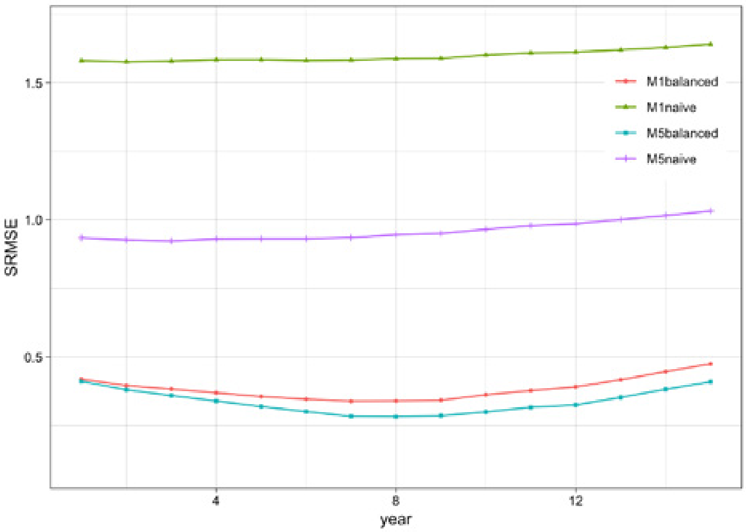

Figure 4: The goodness-of-fit of predicted relative to observed commuting for the 15 years after the opening of the new fixed link. Different model specifications and prediction approaches.

Figure 4 illustrates the prediction accuracy for only two of the model specifications. Predictions based on the competing destinations model, M2, are only marginally more accurate than predictions based on the standard gravity approach, M1. The labor market accessibility measure does not add significantly to the predictability. For a naive prediction approach, the model specification M3, which accounts for some unspecified benefits of residing and working in the same town, performs significantly better than M1 and M2. However, this superiority does not apply to the balanced prediction approach. The model specifications M4, M5, and M6 provide very similar predictions, significantly more accurate than the other model specifications. The benefits of incorporating information on the local housing and labor market conditions are particularly striking for the naive predictions approach. To avoid confusion due to an information overload, only results based on the model specifications M1 and M5 are included in Figure 4, as representatives for their respective groups of similar model specifications, that is, M1, M2, and M3 versus M4, M5, and M6.

There are several points to make from Figure 4:

1. Measured by the SRMSE, the balanced approach persistently provide more accurate predictions of the commuting matrix than the naive approach.

2. The spatial interaction models accounting for within-zone labor and housing market conditions make more accurate predictions of the commuting matrix than the standard doubly-constrained gravity model. This applies to both the naive and the balanced modeling approaches. However, the benefits of extending the model in this direction are, in particular, substantial if a naive prediction approach is employed.

3. In particular, for the balanced prediction approach, there is a clear tendency that the accuracy of the predictions is poorer at the start and at the end of the period under consideration.

It is reasonable to interpret point 3 to reflect the sluggishness in adapting to a new road connection. The new fixed link means that the optimal combination of a residential and a working zone may change for some households. However, it may take a long time before this is turned into action. Selling and buying houses may be time-consuming, and considering new job offers may be a part of the adaption. From an even longer time perspective, the adaption may also be affected by, for example, matching issues in marrying since there is a distance deterrence effect in the choice of partners. This may further cause changes both in the residential location pattern and in the commuting pattern. In general, there are several sources of friction and delayed actions in response to changes in the transportation network. Many of these are inherent in our agent-based data-generating process but not in a doubly-constrained spatial interaction approach. Hence, this is a plausible explanation for why the predictions are inaccurate at the start of the period under consideration. At the same time, the failure to account for the location effects of the exogenous shock contributes to explaining why a doubly-constrained modeling framework engenders inaccurate predictions, particularly after many years of adaption.

7.3.2 Predicting the commuting across the new fixed link

In many applications of spatial interaction models, the primary interest is on the traffic induced for a specific link of the road transportation network rather than on the commuting pattern in general. In principle, an over-prediction of the induced commuting between two towns involving the link may be counteracted by an under-prediction between other towns involving the same link. Hence, errors may cancel each other out, resulting in a reasonably accurate prediction of induced traffic. The opposite is, of course, also possible, that errors reinforce each other into a very biased prediction.

In Figure 5, we consider predictions for aggregate commuting between the two clusters of towns on either side of the former barrier in the road transportation network. In other words, the figure provides predictions for commuting across the new road. Once again, only two model specifications are considered to keep the figure clear and intelligible. The naive approach to making predictions generally performs very poorly, resulting in massive over-predictions of commuting across the new road. This is mainly the case for the model specification M1, which predicts that there will be 7042 commuters using the new road, while the naive application of M5 predicts that the number of commuters for this new stretch of road will be 5681. In this respect, the model specification M2 provides similar results to M1, while the predictions resulting from M3, M4, and M6 do not deviate significantly from the M5-predictions.

Hence, Figure 5 ignores the naive approaches to make predictions and focuses on the balanced versions of the model specifications M1 and M5. Remember from Figure 4 that the model specification M5 provides a significantly more accurate prediction of the commuting pattern than M1, measured by the SRMSE. Hence, it is a surprise that M1 performs better than M5 in predicting the induced commuting across the new road, though the difference is not substan-

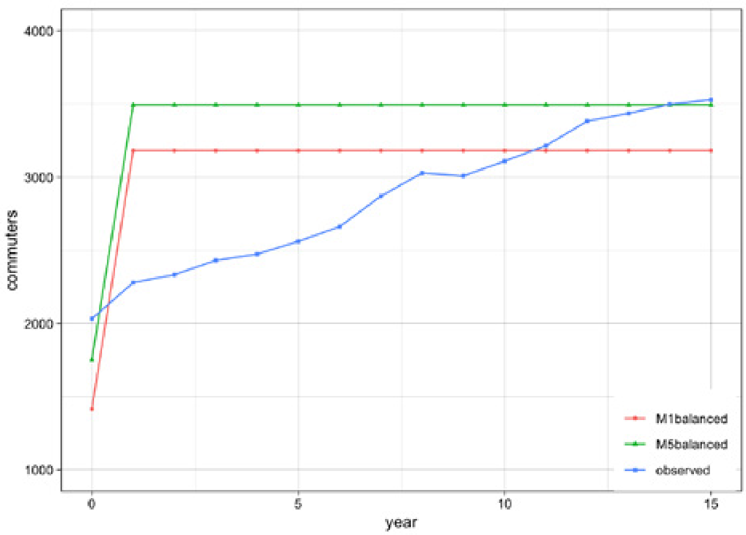

Figure 5: The observed and predicted number of commuters over the 15 years after the opening of the new fixed link.

tial. All the balanced model specifications produced similar predictions of induced commuting. However, the simplest model specification, M1, resulted in a slightly more accurate prediction than all the other model specifications for the 15-year-long period under consideration. This may reflect a case where different errors cancel each other out, providing an accurate aggregate prediction. However, this result also supports a hypothesis that predictions are not very sensitive to the specific choice of a doubly-constrained, gravity-based model specification. The results indicate that the balancing procedure is dominating, working to wipe out differences in predictability resulting from alternative formulations of the structural equation of the model.

Figure 5 shows that both model specifications over-predict induced commuting in a 15-year long time perspective. This pulls in the direction that the benefits of the investments in road transportation infrastructure are over-predicted. Also, notice from the figure that the observed commuting exceeds the predicted commuting only towards the end of the period we are considering. Accounting for the fact that future benefits are discounted at the discount rate in a cost-benefit analysis, this reduces the likelihood of a positive present value of the investments. According to this result, using the gravity-based prediction approach may lead to over-investments in road transportation infrastructure.

The induced commuting in the case of a new road by far exceeds the underlying trend between the two clusters of towns, which was mentioned in Section 7.1. However, remember that this represents just one observation from one specific geography. Also, for this geography, the relocation effects eventually lead to a situation where observed commuting exceeds the predicted commuting. This is, of course, not captured by a doubly-constrained spatial interaction model. In many cases, the relocation effects may be stronger and faster than for the geography used in this analysis, potentially leading to reverse the conclusion of rejecting the investments. Our analysis nevertheless demonstrated that the relocation effects become an increasingly important source of prediction error between the observed and the predicted commuting pattern as time passes.

Welde et al. (2019) studied the capability of planners to predict the traffic induced by new fixed links in Norway. They use data from tunnels and bridges built between 1970 and 2013. Their main finding was that the effects were substantially underestimated in the long term, even in cases where the short-term differences between the predicted and the actual traffic were small. In general, they also report high inaccuracy in the forecasts. They claim that "traffic forecasts in all Norwegian road projects are developed using standardized transport models", under the responsibility of the Norwegian Public Roads Administration. Despite improvements in standard transport models, Welde et al. (2019) find a tendency that forecast accuracy is not improving over time, at least in the period 1989-2013.

Welde et al. (2019) mention the Great Belt fixed link in Denmark, where the traffic was more than 70% higher than planned one year after the opening. This increase has been explained to reflect increased economic activity resulting from the new bridge. The Øresund bridge between Sweden and Denmark had 20% lower traffic than expected just after the opening, but after three years, the traffic was higher than the ex-ante prediction. These results are in line with results presented by Odeck and Welde (2017), who also found that the level of underprediction is higher in the long than in the short-term time perspective. Based on 12 studies from other countries, Nicolaisen and Driscoll (2014), on the other hand, found that induced traffic was consistently overpredicted.

8 Predicting commuting flows for another agent-based dataset

The agent-based approach provides a dataset resulting from complex labor and housing market interactions between the agents. The estimation results and the predictions discussed in Section 4 and Section 7, respectively, represent just one realization of the simulation experiment, that is, one observation of the 12-node geography. In principle, it is possible to generate numerous simulation experiments, providing datasets representing observations from different geography specifications. This allows studying systematically how spatial structure characteristics affect the ability of a spatial interaction model to make accurate predictions of, for example, induced commuting resulting from a new fixed link. Does it, for instance, matter to what degree the new fixed link connects a rural area to a dominating regional center? In practice, the number of cases to study is limited by the running time of generating data sets. For the reasonably large system considered above, with many complex decisions to be made by many agents, it is relatively time-consuming to generate data for a specific scenario. This paper considers the results from one case in addition to the case discussed in Sections 4 and 7. This at least gives an idea of how sensitive the predictability is to the specification of the transportation network and the housing and labor market conditions.

This section studies a slightly more unbalanced system than the previous sections, primarily because more jobs are concentrated in the regional center. We made the following adjustments:

- a 33% increase in transportation costs per unit of distance
- a more centralized spatial distribution of basic sector jobs, with 600 more jobs in the CBD, that is, town E and a corresponding reduction in the towns A, B, and D in the peripheral part of the region
- the parameters of the function determining the spatial distribution of local sector activities are changed in a direction where consumers in neighboring towns do more of their shopping in the regional center, reflecting stronger economies of scale and scope in shopping
- initial wages are reduced by 10% in all the four towns in the peripheral part of the region, and the unemployment insurance is reduced by 25%
- the initial housing stock is considerably increased in the regional center

- the distances from the peripheral part of the region to the nearest town in the rest of the system is assumed to be 60 km, rather than 45 km from town C to town E and 75 km from town A to town G

Remember from Section 7.1 that M5 also did better than M1 in predicting the total commuting between the two clusters of towns, which are separated by the topographical barrier. This improvement in predicting the base year commuting is even more substantial for the new scenario. The agent-based data generation gives an observed number of 3709 commuters between the two clusters of towns. The standard doubly constrained gravity model predicts the number of interarea commuters is just 2075, while the model formulation M5 predicts 3368 commuters between the two areas. Hence, accounting for spatial disparities in wages and housing prices contributes to a more accurate prediction of the observed commuting flows in year 0.

As a next step, the two model formulations are used to predict the number of interarea commuters where a new fixed link leads to a substantially shortened road connection between the towns at either side of the topographical barrier. Consider first the instant effect on commuting that is, the interarea commuting in year 1. First, this unbalanced system has more interarea commuting than in the benchmark scenario discussed in Section 7. In this new case, the observed number of commuters between the two towns at either side of the barrier was 3709 prior to the investments in the new fixed link and 4045 in year 1, that is, in the first year after the new fixed link is established. Remember that the corresponding numbers were 2031 and 2279 in the case we studied in Section 7.

Consider once again the predicted increase in commuting provided by the modeling alternatives M1 and M5. Based on a naive approach, the standard doubly-constrained gravity model (M1) severely over-predicts the increased commuting by predicting 11920 commuters across the new fixed link in year 1. The prediction is substantially lower when the balanced version of M1 is being used, with just 3081 commuters predicted to commute across the new fixed link. The predictions based on the model formulation M5 align with the observed number of 4045 commuters in year 1. The balanced version of M5 predicts that there will be 3898 interarea commuters in year 1, while the naive approach predicts 4696 commuters using the new link.

There are many useful insights gained from these results. First, accounting for spatial disparities in housing prices and wages provides significantly more accurate predictions from the spatial interaction model. This applies both for

- the overall commuting pattern in the base year
- the commuting between the two clusters of towns, in the base year
- the overall commuting pattern in the first year after the new fixed link is established between the towns B and E
- the instant increase in commuting induced across the new fixed link

In addition, the results demonstrate that the naive approach is, in particular, naive in the case of a standard doubly-constrained model formulation. To a large degree, accounting for spatial variation in wages and housing prices substitutes the effect of the balancing factors in the spatial interaction model. Still, the balanced version of model formulation M5 is superior to the naive version. The local wage, measured relative to the local housing price, $\frac{W}{H}$, is estimated to significantly and strongly affect the spatial labor market interaction. This reflects the tendency for workers to be attracted to an OD combination of towns where the housing prices are low at the residential site and the wages are high at the job location. Accounting for this effect contributes to a better understanding and more accurate predictions of commuting patterns.

Also, for this more unbalanced geography, we consider a time perspective beyond the instant effect of the new fixed link. For our new experiments, the evaluation of the predictability of the overall commuting pattern is very similar to the discussion in Section 7.3.1. We do not enter further details on this discussion and move directly to the predictability of the induced commuting across the new fixed link. Figure 6 demonstrates that the balanced M1 and M5 predict less than the observed commuting across the new fixed link for the 15-year-long period under consideration.

The model formulation M5 is substantially more accurate than the standard doubly-constrained gravity model, also in the long run time perspective illustrated in Figure 6. This again demonstrates the need to account for spatial wage disparities and housing prices in modeling spatial labor market interaction. As illustrated in Figure 6, the model formulation M5 provides an accurate prediction of the induced commuting, particularly in the first year after the opening of the new fixed link. This indicates that the model captures the effect of the more unbalanced spatial distribution of jobs and houses underlying the data-generating simulation experiment.

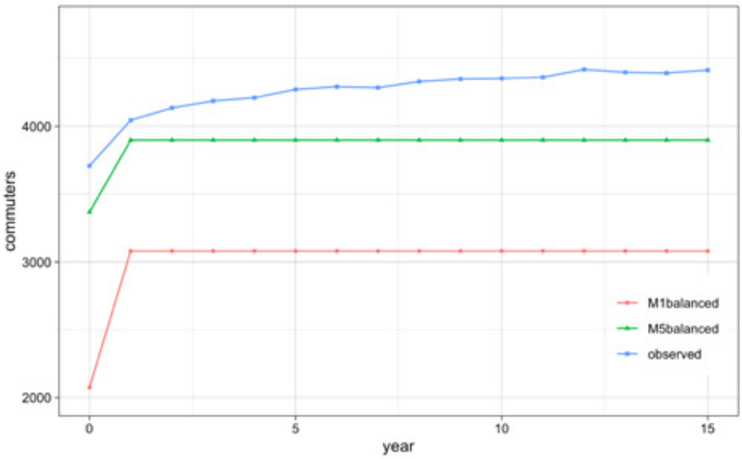

Figure 6: The observed and predicted number of commuters over the 15 years after the opening of the new fixed link. A case with a more unbalanced spatial distribution of jobs than in the case studied in Section 7.

Our results also demonstrate that spatial disparities in wages and housing prices, accompanied by asymmetries in the distribution of jobs and houses, are, in general, not adequately captured by the balancing factors in a spatial interaction model.

Figure 6 further illustrates that the tendency of under-predicting induced commuting increases as years go by after the opening of the new fixed link. This reflects the effects of the relocation decisions of the agents, that is, the effects of the wider local impacts. From a dynamic perspective, utility-maximizing workers continuously search for better jobs and residential location combinations. The new fixed link represents an opportunity to live in an area with lower housing prices while commuting to job locations offering high wages. In line with bid rent theory, this suggests a process of urban sprawl and growth in rural areas. This effect is not very strong in any of the simulation experiments considered in this paper. However, it is more apparent in the scenario illustrated in Figure 5 than in the case illustrated in Figure 6. Nevertheless, it reinforces the tendency that using a spatial interaction model under-predicts the willingness to pay for a new fixed link in the unbalanced geography considered in Figure 6. Relocation effects are, of course, not captured by the family of simple spatial interaction models.

9 Observed local population growth in a region where several fixed links have been established

As mentioned in Section 2, the literature provides a very mixed picture of how investments in transport infrastructure affect the local growth in employment and population. Still, there is a consensus that new fixed links trigger population growth, particularly in cases where a rural area is getting substantially better linked to a dominating, larger labor market area; see, for instance, Welde and Tveter (2022). In this section, we consider the population growth of some municipalities in a region where investments in several fixed links over the last 50 years have resulted in an extended and better-integrated labor market area.

The agent-based simulation experiments considered in the sections 7 and 8 were run for a relatively sparsely populated region. The investments in the fixed link did not connect the most peripheral area to a dominating urban area. Nevertheless, the new link connects the peripheral area to the regional center, and the data generated demonstrated that the number of commuters tends to increase as time passes after the link's opening. This reflects that agents are taking advantage of new labor market opportunities, explaining wider local impacts regarding increased local population growth.

Figure 7 provides a map of some of the municipalities in the Bergen labor market area for the situation prior to a recent merging of a few municipalities. As an early significant change in the transport network in this area, the Sotra bridge connected the municipality of Fjell to the mainland in 1971. This bridge substantially reduced the traveling time to Bergen, the second-largest city in Norway. In the 80s and 90s, Øygarden was also connected to the Sotra bridge and the mainland by constructing a series of bridges and tunnels.

Figure 8 illustrates the explosive population growth in the municipality of Fjell after 1970. Figure 9 illustrates the percentage population growth after 1964, compared to the percentage population growth in Norway and in addition for the two neighboring municipalities Sund and Øygarden. These two municipalities have also been connected to the mainland, but at a longer distance from Bergen than what is the case for Fjell.

The municipalities north of Bergen benefitted from the Nordhordland Bridge, which was opened in 1994, connecting the Nordhordland region to Bergen. This new fixed link was a bridge from the northern part of the municipality of Bergen and the southern part of Meland; see the

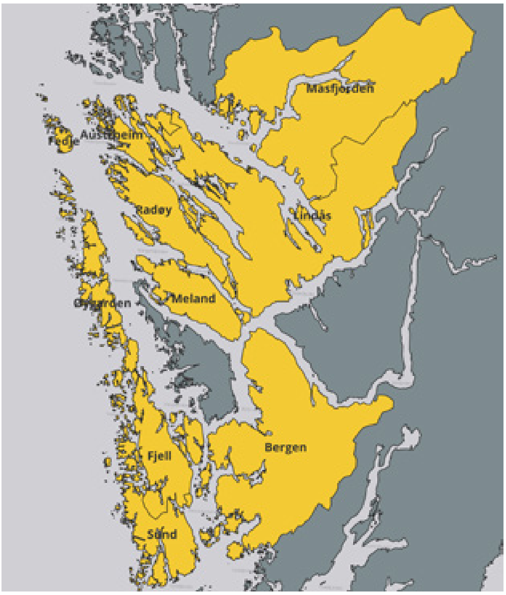

Figure 7: Some of the municipalities in the Bergen region in 2018.

map in Figure 7. Figure 10 illustrates the percentage population growth of some municipalities in Nordhordland in the years after 1964, compared to the national population growth in this period.

Notice that there has been a massively increased population growth in some of the municipalities after the new fixed links opened. This, in particular, applies to Fjell and Meland, the two municipalities located closest to the fixed link represented by the Sotra Bridge and the Nordhordland Bridge, respectively. The municipalities of Sund and Lindås have also experienced a population growth considerably higher than the national population growth.

This descriptive approach does not prove anything but provides a rationale for some reasonable hypotheses on the general effect of investments in fixed links and on the use of spatial interaction models to predict induced commuting. It is unlikely to be due to a mere coincidence that the size of the population growth of the different municipalities in Nordhordland seems to be systematically negatively related to the distance from the Nordhordland Bridge, and similarly for the municipalities benefitting from the Sotra Bridge. The observations further support a hypothesis that a new fixed link induces substantial population growth in rural areas getting considerably better connected to a large and dynamic urban area. Hence, the observa-

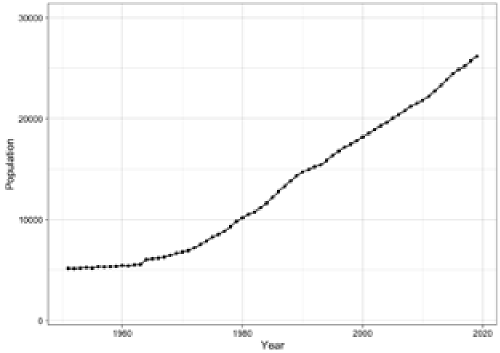

Figure 8: The population development in the municipality of Fjell from 1951 to 2019, when Fjell was merged with two other municipalities. In 1971, Fjell was connected to the mainland by a bridge.

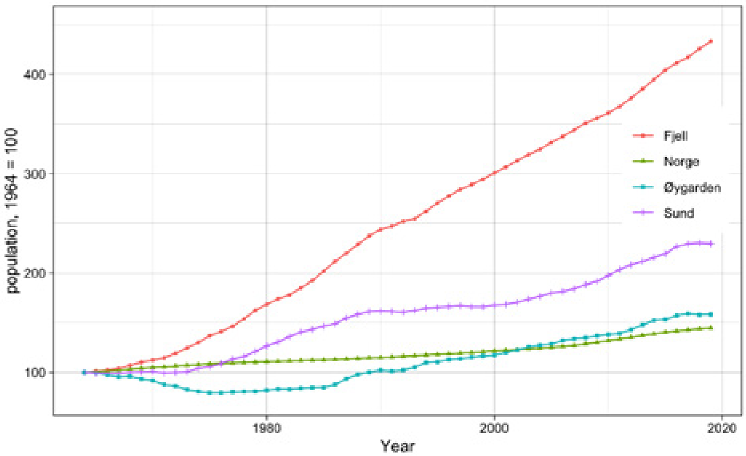

Figure 9: The population development in the municipalities of Fjell, Sund and Øygarden from 1964 to 2019, compared to the national population growth. 1964=100.

tions provide a rationale to question the value of a spatial interaction model as a framework for estimating the willingness to pay for road investments in such a scenario.

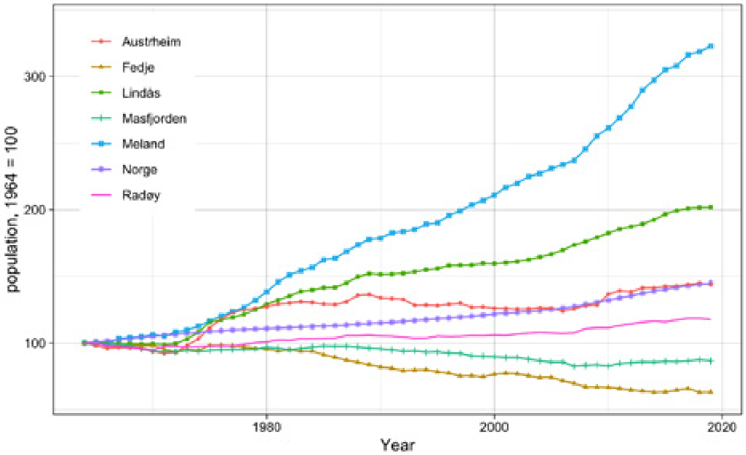

Figure 10: The population development in different municipalities in Nordhordland from 1964 to 2019, compared to the national population growth. 1964=100.

For the geography and the transport network considered in Section 7, the relocation effects following the new fixed link were slow. It took a long time before the relocation effects were dominating. Hence, for the 15-year-long period under consideration, the induced commuting was over-predicted, contributing to an over-evaluation of the benefits of the investments in road transport infrastructure. It is possible to find scenarios, both in an agent-based synthetic modeling framework and in the real world, where the relocation effects are faster and much stronger than for the two cases under consideration in this paper. In some cases, sparsely populated areas have been connected to urban areas by a new bridge or tunnel, providing job opportunities within a reasonable commuting distance. The Bergen labor market area examples indicate that such investments may induce a very rapid local population growth. In such cases, a doubly-constrained spatial interaction modeling framework may severely under-predict induced commuting, potentially leading to a false conclusion that the benefits of the investments are considerably lower than the costs. Hence, this may lead to unfortunate investment decisions, for instance, in the form of an undersized road network. A new Sotra Bridge is being planned due to capacity limits and congestion problems in the current situation. In general, accurate predictions are important in a long-term planning perspective.

10 Concluding remarks

The analysis in this paper has demonstrated the effects of significant challenges and modeling issues in predicting induced commuting from spatial interaction models. One specific and expected result is that it is crucial to explicitly account for the balancing constraints in explaining and predicting the commuting pattern. Another lesson from the experiments is that incorporating relevant information on labor and housing market conditions significantly explains the commuting pattern.

The balancing constraints' effect dominates, particularly in predicting induced commuting for a specific stretch of road. In this paper, we have been considering two realizations of a 12-node geography. Both cases are realistic, but our benchmark scenario represents a more balanced situation regarding how jobs are distributed across the 12 towns. This benchmark case provides an example of how the simple, standard doubly-constrained gravity model predicts induced commuting more accurately than more advanced and theoretically more satisfying model specifications. Hence, from a pragmatic point of view, striving for model specifications with the highest possible explanatory power only pays off if the primary ambition of the analysis is to make accurate predictions of induced commuting. According to Nicolaisen and Driscoll (2014), this is in line with other literature on travel demand, but it is not supported by the other case considered in this paper.

The standard doubly-constrained gravity model performs reasonably well in explaining the observed commuting pattern at the point in time when data were collected. Still, accounting for spatial structure as well as labor and housing market conditions contributes to more accurate predictions of commuting between the two clusters of towns on either side of the topographical barrier. However, a challenge is that the accuracy of the predictions deteriorates over time due to continuous changes in the location system of an inherently dynamic system, like the agent-based modeling framework, and, of course, like in a real-life scenario.

The main issues in this paper are related to out-of-sample predictions, represented by the effects of investments in road infrastructure on the commuting pattern in general and the number of commuters on the new fixed link. Concerning the immediate effects of road investments, our experiments demonstrate the importance of considering balancing constraints in providing predictions both for the commuting pattern in general and for the induced commuting on the new fixed link in particular. The poor performance of an approach that ignores the effects of the balancing constraints is also valid in making predictions of commuting in a longer run-time perspective. Still, the predictions become more accurate if local labor and housing market conditions are accounted for. However, a balanced approach to making predictions is still superior to a naive approach that ignores the balancing constraints. As for the balanced approach, the accuracy of predicting a commuting pattern tends to be poorer at the start and the end of the period under consideration. This reflects a failure to capture the sluggishness in adapting to a new road connection and disregarding the exogenous shock's location effects. The location effects are particularly expected to be evident in a relatively long-term perspective.

As mentioned above, our experiments provide an example where the standard doubly-constrained gravity model performs better than more advanced model specifications in predicting induced commuting on a new road connection. This is even though extended model specifications perform significantly better in predicting the commuting pattern in general. Hence, the model specification that performs best to explain commuting is not necessarily superior in making predictions of induced commuting. It is a reasonable hypothesis that this emerges from the failure of any doubly-constrained spatial interaction model to capture relocation effects.

Our simulation results indicate that there are, in particular, two severe sources of bias in predicting induced commuting on a new fixed link. One is related to the spatial distribution of jobs. The predictability of the spatial interaction models is demonstrated to differ between the benchmark scenario and a more unbalanced, centralized case, where a higher proportion of the jobs is located in the regional center. In the unbalanced case, the standard doubly constrained gravity model performs poorly in predicting induced commuting on the new fixed link. In this case, the predictability benefits considerably from accounting for spatial disparities in wages and housing prices. The unbalanced system is reflected in wages and housing prices and further in the spatial interaction behavior of workers. This is not necessarily captured by the balancing factors of a standard spatial interaction model. However, our results indicate that a careful formulation of the spatial interaction model has the potential to deal with problems stemming from an unbalanced system. Still, adjusting for spatial disparities in housing prices and wages is a rare practice in the empirical spatial interaction literature. Our experiments demonstrate that this failure may cause significant prediction errors. In the unbalanced case studied in Figure 6, failing to account for housing prices and wages proved to reinforce the under-predictions of the willingness to pay for a new fixed link.

It is, in general, more difficult to account for the other primary source of prediction bias by using a spatial interaction model, which is related to the wider local impacts of the investments in transport infrastructure. In the two agent-based scenarios we discussed, the relocation effects of the new fixed link were limited. Still, such relocation effects explain a substantial increase in interarea commuting over time, as workers take advantage of new options in combining residential and job locations, and local sector firms adopt to changes in the residential location pattern. This is, of course, not captured by a doubly-constrained spatial interaction model, and our agent-based experiments demonstrate that this is a severe source of prediction bias. We also address empirical observations from a Norwegian labor market area where innovations in the transport network have led to substantial reductions in commuting time from previously isolated rural areas to the dominating urban center. These observations indicate the potential for road investments to induce commuting resulting from relocation effects, which may completely dominate the instant effect of a new fixed link on spatial labor market interaction. In such cases, new areas appear as attractive combinations of housing prices and commuting costs, explaining a process of urban sprawl and wider local impacts. These effects leave predictions based on traditional spatial interaction models inadequate, representing approaches resulting in massive under-predictions of induced commuting and the willingness to pay for a new fixed link. Hence, such methods should be used with care, particularly in cost-benefit appraisals of projects that substantially improve the labor market accessibility of a previously rural area. In assessing 38 fixed links in Norway, Welde and Tveter (2022) found that the labor market is, as a rule, relatively static, especially in the short run, and that only a few cases achieve significant commuting effects.

Mass media often focus on errors in estimating the costs of building new roads. In many cases, this focus must be balanced against the risk of failing to make reliable predictions of the induced traffic and the benefits of the investments. Estimating demand and induced traffic may be more complex than cost calculations, often involving more uncertainty. In many cases, relocation effects will not be significant (Welde & Tveter, 2022)), but they sometimes seriously complicate traffic predictions and benefits. Such effects are not captured by a doubly-constrained spatial interaction model. Hence, in evaluating the benefits of investments in transport infrastructure, it is strongly recommended that reliable general spatial equilibrium models be developed and used more regularly. This can be along the lines suggested by McArthur et al. (2014), who provide a modeling framework designed for a rural context, like a typical Norwegian region. This paper has demonstrated that the pay-off of reaching more accurate predictions of relocation effects may substantially exceed the pay-off of formulating more advanced spatial interaction models. Nicolaisen and Driscoll (2014) pointed out that a tendency to underestimate demand for road projects means that capacity limits may be met earlier than predicted, calling for expensive capacity expansions.

As a closing statement in their literature review, Nicolaisen and Driscoll (2014) find it relevant to inquire whether demand forecast accuracy can be significantly be improved, recognizing that inaccuracy has been a problem for several decades, despite continuous improvements in forecasting techniques. They further refer to Hartgen (2013), who outlines a humility approach for planning research and practice, which focuses on quantifying the uncertainty, recognizing the inaccuracy, and recommending that forecasts have a reduced impact on decision-making. In discussing alternative approaches, remember that the agent-based modeling framework for a synthetic population can be designed and applied to provide instrumental analyses and predictions of how road investments affect the location pattern and traffic. This paper uses the agent-based approach to generate data for evaluating spatial interaction models. However, it is, at the same time, a spatial general equilibrium model, that is a Land Use/Transport Interaction model (LUTI). As such, it represents a relevant approach to making travel demand predictions that account for the effects of relocations and changes in land use. Through a meticulous formulation of the geography and the population, and simulation experiments aimed at the most ambiguous elements, such an approach is well suited to address uncertainty and forecasting inaccuracies. An agent-based approach has the potential to contribute with reasonable forecasts on traffic increase and benefits resulting from constructing new fixed links in the transportation network.

References

[1] Abadie, A, A Diamond, and J Hainmueller, 2010, "Synthetic control methods for comparative case studies: Estimating the effects of Californias tobacco control program", *Journal of the American Statistical Association*, 105, 403-505.

[2] Anas, A, 1983, "Discrete choice theory, information theory and the multinomial logit and gravity models",*Transportation Research B*, 17, pp. 13-23.

[3] Brueckner, J K, 2011, *Lectures on Urban Economics*, The MIT Press

[4] Capello, R, 2016, *Regional Economics*, Routledge

[5] Chatman, D G, and Noland, R B, 2011, "Do public transport improvements increase agglomeration economies? A review of literature and an agenda for research", *Transport Reviews*, 31(6), 725-742.

[6] Deng, T, 2013, "Impacts of Transport Infrastructure on Productivity and Economic Growth: Recent Advances and Research Challenges ", *Transport Reviews*, 33(6), 686-699.

[7] Crescenzi, R, M Di Cataldo, A Rodriguez-Pose, 2016, "Government quality and the economic returns of transport infrastructure investment in European regions", *Journal of Regional Science*, 56, 555-582.

[8] Donaldson D, 2018, "Railroads of the Raj: Estimating the impact of transportation infrastructure", American Economic Review, 108, 899-934.

[9] Duranton, G, and Puga, D, 2004, "Micro-foundations of urban agglomeration economies". In J Vernon Henderson and Jacques-Francois Thisse (Eds.), *Handbook of regional and urban economics* (Vol. 4, pp. 2063-2117). Amsterdam: Elsevier B.V.

[10] Elburz Z, P Nijkamp, E Pels, 2017, "Public infrastructure and regional growth: Lessons from meta-analysis", Journal of Transport Geography, 58, 1-8.

[11] Ellison, G, Glaeser, E L, and Kerr, W, 2007, "What causes industry agglomeration? Evidence from coagglomeration patterns", NBER Working Paper 13068.

[12] Eliasson, J, M Börjesson, J Odeck, and M Welde, 2015, "Does benefit/cost efficiency influence transport investment decisions?" *Journal of Transport Economic Policy*, 49 (3), 377-396.

[13] Erlander, S and N F Stewart, 1990, "The Gravity Model in Transportation Analysis — Theory and Extensions", VSP, Utrecht.

[14] Fotheringham A S, 1983b, "A new set of spatial interaction models: the theory of competing destinations", *Environment and Planning A*, 15,15-36.

[15] Fotheringham A S, 1986, "Modelling hierarchical destination choice", *Environment and Planning A*, 18, 401-418.

[16] Gitlesen J P and I Thorsen, 2000, "A Competing Destinations Approach to Modeling Commuting Flows: A Theoretical Interpretation and An Empirical Application of the Model", Environment and Planning A, 32, 2057-2074.

[17] Gjestland, A, I Thorsen, and J Ubøe, 2006, "Some aspects on the intraregional spatial distribution of local sector activities", *Annals of Regional Science*, 40, 559-582.

[18] Gjestland, A, D P McArthur, L Osland, and I Thorsen, 2014, "The suitability of hedonic models for cost-benefit analysis: Evidence from commuting flows", *Transportation Research Part A*, 61, 136-151.

[19] Gholami, A, I Thorsen and J Ubøe, 2023, "An agent-based approach to study spatial structure effects on estimated distance deterrence in commuting.", ...

[20] Gholami, A, I Thorsen and J Ubøe, 2023b, "An experimental approach to study how commuting behaviour reflects preferences, labour market conditions and housing prices", ...

[21] Gibbons, S, T Lyytikäinen, H G Overman, R Sanchis-Guarner, 2019, "New road infrastructure: The effects on firms", *Journal og Urban Economics*, 110, 35-50.

[22] Graham, D J, 2007, "Agglomeration, productivity and transport investment", *Journal of Transport Economics and Policy*, 41, 317-343.

[23] Graham, D J and S Gibbons, 2019, "Quantifying wider economic impacts of agglomeration for transport appraisal: existing evidence and future directions." *Economics of Transportation*, 19, 100121.

[24] Gühneman, A, J J Laird, and A D Pearman, 2012, "Combining cost-benefit and multi-criteria analysis to prioritise a national infrastructure programme", *Transport Policy*, 23, 15-24.

[25] Hartgen, D T, 2013, "Hubris or humility? Accuracy issues for the next 50 years of travel demand modelling", *Transportation*, 40 (6), 1133-1157.

[26] Hensher, D A, Truong, T P, Mulley, C, and Ellison, R, 2012. "Assessing the wider economy impacts of transport infrastructure investment with an illustrative application to the North-West Rail Link project in Sydney, Australia", *Journal of Transport Geography*, 24, 292-305.

[27] Kasraian D, K Maat, D Stead and B van Wee, 2016, "Long-term impacts of transport infrastructure networks on land-use change: an international review of empirical studies", *Transport Reviews*, 36(6), 772-792.

[28] Knudsen, C D, and A S Fotheringham, 1986, "Matrix comparison, goodness-of-fit and spatial interaction modeling", *International Regional Science Review*, 10, 127-147.

[29] Locatelli G, D C Invernizzi, N J Brookes, 2017, "Project characteristics and performance in Europe: An empirical analysis for large transport infrastructure projects", *Transportation Research Part A: Policy and Practice*, 98, 108-122.

[30] Maparu T S and T N Mazumder, 2017, "Transport infrastructure, economic development and urbanization in India (1990-2011): Is there any causal relationship?", *Transportation Research Part A: Policy and Practice*, 100, 319-336.

[31] McArthur, D P, I Thorsen, and J Ubøe, 2020, "Some consequences of ignoring relocations in the cost-benefit analysis of transportation infrastructure investments", in Thill, J-C, *Innovations in urban and regional systems: contributions from GIS&T, spatial analysis and location modeling*, Springer, 137-164.

[32] McCann, P, 2013, *Urban and Regional Economics*,

[33] Melo, P C, Graham, D J, and Noland, R B, 2009, "A meta-analysis of estimates of urban agglomeration economies", *Regional Science and Urban Economics*, 39(3), 332-342.

[34] Melia, S, 2018, "Does transport investments really boost economic growth? " *World Transport Policy & Practice*, 23, 118-129.

[35] Nicolaisen, M S and P A Driscoll, 2014, "Ex-post evaluations of demand forecast accuracy: a literature review". *Transport Reviews*, 34 (4), 540-557.

[36] Odeck, J and M Welde, 2017, "The accuracy of toll road traffic forecasts: An econometric evaluation", *Transportation Research Part A*, 101, 73-85.

[37] Oosterhaven, J, and T Knaap, 2003, "Spatial economic impacts of transport infrastructure investments", in A Pearman, P Mackie, J Nellthorp and L Giorgi (Eds.), *Transport projects, programmes and policies: evaluation needs and capabilities*, pp. 87-100, Aldershot: Ashgate.

[38] Saidi S, M Shahbaz, and P Akhtar, 2018, "The long-run relationships between transport energy consumption, transport infrastructure, and economic growth in MENA countries", *Transportation Research Part A: Policy and Practice*, 111, 78-95.

[39] Small, K.A., Verhoef, E.T., 2007, *The Economics of Urban Transportation*, Psychology Press.

[40] Sen, A and T Smith, 1995, *Gravity Models of Spatial Interaction Behavior*, Springer-Verlag, Berlin and Heidelberg.

[41] Siemiatycki, M, 2009, "Academics and auditors. Comparing perspectives on transportation project cost overruns", *Journal of Planning Education and Research*, 29 (2), 142-156.

[42] Thorsen, I, and J P Gitlesen, 1998, "Empirical Evaluation of Alternative Model Specifications to Predict Commuting Flows", *Journal of Regional Science*, 38, 273-292.

[43] Tveter, E, M Welde, and J Odeck, 2017, "Do fixed links affect settlement patterns: a synthetic control approach", *Research in Transport Economics*, 63, 59-72.

[44] Tveter, E, 2020, "Explaining differences in ex-anta calculations of wider economic impacts: a review of 55 calculations." *Case Studies on Transport Policy*, 8 (4), 1401-1411.

[45] Tveter, E and J Laird, 2018, “Agglomeration - How long until we see the benefits¿‘*Scottish Transport Applications and Research Conference (STAR)*”, Caledonian University, Glasgow.

[46] Venables, A J, 1996, “Equilibrium locations of vertically linked industries”, *International Economic Review*, 37, 341-359.

[47] Venables, A J, 2007, “Evaluating urban transport improvements: Cost-benefit analysis in the presence of agglomeration and income taxation”, *Journal of Transport Economics and Policy*, 41(2), 173-188.

[48] Wang, C, M K Lim, X Zhang, L Zhao, P T Lee, 2020, “Railway and road infrastructure in the Belt and Road Initiative countries: Estimating the impact of transport infrastructure on economic growth”, Transportation Research Part A, 288-307.

[49] Wangsness, P B, K L Rødseth, and W Hansen, 2017, “A reivew of guidelines for including wider economic impacts in transport appraisal”, *Transport Reviews*, Volume 37, 1.

[50] Welde, M, E Tveter, and J Odeck, 2019, “The traffic effects of fixed links: short and long-run forecast accuracy”, *Transportation Research Procedia*, 42, 64-74.

[51] Welde, M and E Tveter, 2022, “The wider local impacts of new roads: A case study of 120 projects”, *Transport Policy*, 115, 164-180.

[52] Wilson, A, 2010, “Entropy in urban and regional modelling: Retrospect and prospect”, *Geographical Analysis*, 42, 364-394.