Rural Decline and Residential Sorting

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JEL Classification: R11, R21, R23, R51, R53.

Keywords: Dynamic Residential Sorting, Rural Decline, Local Amenities, Tiebout Sorting.

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1 Introduction

The trend towards urbanization that pervades in the developed world began hundreds of years ago, first as a result of the development from agrarian to industrialized economies, and subsequently to computerized, and now digitalized economies. In consequence, most developed countries have experienced a significant decline in the share of populations living in rural areas, and over the past decades, it has been common to observe rural areas in decay as people move to urban areas or metropoles. For the OECD countries overall, the rural share of the population was 38% in 1960 and 18% in 2024, see Figure 8 in the supplementary material.[1] It is primarily the younger generations that move away from rural areas to urban living, and consequently, the demographic trend of aging populations is much stronger in rural areas than in metropoles.

Within country divergence of growth and income is a potential source of tension that may be detrimental to people's sense of social cohesion and fairness (see e.g. Wirth et al. (2016), Inglehart and Norris (2016), and Protzer (2021)), and this underscores the importance of understanding rural decline. Yet knowledge about the costs of depopulation is lacking and the basis for decision-making consequently poor.[2]

In this paper, we formulate and estimate a structural dynamic model of residential sorting with special emphasis on rural areas. The model allows us to compute the willingness-to-pay for selected local public services and amenities, such as the existence of a local school, local grocery store, local job market conditions, and distance to emergency room (ER) unit. The paper uses detailed information on home prices for all owner-occupied homes (apartments and houses) in Denmark over a period of 31 years (1992-2022), including detailed annual information about the households living in these

[1] Source: The World Bank Databank on Health Nutrition and Population Statistics.

[2] A spatial form of inequality described as "peripheralisation", whereby rural areas become decoupled from a centralization process, is considered in rural sociology, see Wirth et al. (2016). Also see Brown and Swanson (2002) and the series of decennial edited anthologies from the Rural Sociological Society starting with Dillman and Hobbs (2019) (first published in 1982).

homes.

We find that, over time, rural schools close, distances to ER units increase, local labor markets develop very differently throughout the nation, and local access to grocery stores declines in rural areas.

Based on a dynamic model of residential sorting, we compute willingness-to-pay (WtP) for local services and amenities. The amenities included here all turn out to be highly significantly important with the exception of distance to nearest ER unit, which is insignificant in the utility model. Transforming per-period utility values to pecuniary WtP and computing the net present value, we find relatively large but plausible estimates for feeder schools and schools with 1-9 – in the range of USD 30,000-50,000. Similarly, an additional 1,000 workplaces within a one hour commuting zone from own neighborhood is valued at about USD 3,500-6,150. The point estimate for grocery stores indicates a net present value of USD 77,000. Although the existence of a local grocery store likely is valued relatively high, this estimate appears excessive.

This article departs from the existing literature in three important ways. First, prior research on dynamic residential sorting has been limited to metropolitan and larger urban areas, see e.g. Kuminoff et al. (2013), Bayer et al. (2016), and Carstensen et al. (2022), and optimal interstate migration, Kennan and Walker (2011). In this paper, we use nationwide data, but with a focus on rural areas. Second, the link between residential decisions and local public services and amenities is at the core of the vast literature on Tiebout sorting, e.g., Tiebout (1956), Rhode and Strumpf (2003), Oates (2006), Bayer and Timmins (2007), Banzhaf and Walsh (2008), and Currie et al. (2015). As pointed out by Banzhaf and Walsh (2008), direct tests of actual migratory responses to provision of local public services and amenities are rare. As an addition to the literature, we provide this in a dynamic and rural context where neighborhood characteristics also impact individuals' formation of expectations concerning future house prices. Lastly, the literature on "place-based" policies, which target transfers toward particular geographic areas rather than groups of individuals, is of relevance to this study, see e.g. Glaeser and Gottlieb (2008), Rossi-Hansberg et al. (2010), Busso et al. (2013), and Manning and Petrongolo (2017).

The rest of the paper proceeds as follows. Section 2 describes the data. In section 3 we present the model and our identification strategy while section 4 describes the estimation. Section 5 presents the results, and in section 6 we discuss the findings and policy implications, discusses relevant extensions to this current analysis, and conclude.

2 Data and descriptive statistics

This study is based on administrative records from Statistics Denmark. The data include all persons and all owner-occupied houses and apartments, i.e. a complete panel data set with annual observations over 31 years from 1992 to 2022.

The administrative estate data include detailed information on all owner-occupied homes, including an assessed value for each year. These assessments, made for tax purposes, are relatively close to actual selling prices but tend to underestimate them slightly. Hence, we adjust the assessed prices with the percentage deviance between assessed and actual selling price among the houses sold locally that year.[3] Detailed individual information exists on all owners, buyers, and sellers, and these socioeconomic characteristics have been merged with the estate data.

The administrative records on the population include all individuals aged 16 years and older. For our modeling purposes, this means that we follow families and their composition over time. This is possible as each person has a unique central personal register (CPR) number which is used to identify the person across registries and over time. Data on individuals and families include detailed information on demographics and

[3]See the supplementary material for further details.

socioeconomic covariates, including education, labor market history, income, wealth, age, and age of children. Data on all workplaces, public and private, also exist, and we utilize this information to compute the number of relevant jobs within a one-hour commuting distance for persons at any given address. We also make use of these data to observe local grocery store.

2.1 Parishes as neighborhoods

In the literature on residential sorting, see Kuminoff et al. (2013) for a review, the tradition is to label the geographical model entities as "neighborhoods". In the present paper, we define our neighborhoods in terms of parishes.[4] For our purpose, parishes are useful as neighborhoods for three reasons. First, they are relatively small in size but big enough to have a number of households moving in and out every year, and big enough to sometimes, but not always, have a local school and/or local grocery store. Second, they do not cross municipal borders, and residents in a parish are therefore under the same local jurisdictional entity and pay the same level of municipal tax. Third, the parishes can be subdivided into types of parish according to how geographically remote they are from major cities, and, for our model, this is a very useful sub-categorization.[5]

The parishes are divided into one of four types that vary by population density: urban cities; urban towns; rural, close to cities; and, rural, far from cities.[6]

In our data for 2014, there are 2,085 parishes with an average parish (neighborhood) size of 7.6 square miles. A parish can change over time, but we have access to exact and

[4] Interchangeably, we use the terms "parish", "neighborhood" and "local community".

[5] Historically, parishes used to be so-called "parish-municipalities", which meant that they had many of the obligations found in municipalities today, including offering public schooling. In 1970, a structural reform was implemented, which reduced the number of municipalities from 1,098 to 277 municipalities. As of April 1, 1974 this was further reduced to 275. At the same time, the parishes became "church parishes" with no secular administrative obligations.

[6] Details are given in the Supplementary Material. A fifth parish category is Small islands, which is excluded from the analysis.

unique dwelling numbers and can therefore uphold the 2014 parish definition and also include new dwellings.

2.2 Neighborhood characteristics

The amenities and public service characteristics of each neighborhood in the model include measures of access to jobs, distance to nearest emergency room unit (ER unit), as well as the existence of a local school and grocery store. The definition and construction of these neighborhood characteristics is as follows.

The measure of access to jobs is based on travel time distances computed for all parish-to-parish combinations and linked to the administrative information on number and type of employees. This enables us to compute the number of workplaces within a one-hour commute between all parishes.[7] Access to jobs is computed for each parish and for high- and low-skilled workers (more details given in the Supplementary Material). Second, we track the parishes of all ER units over time, and apply the computed parish-to-parish travel time distances to compute the time distance to the nearest ER unit across parishes and time.[8] Third, across years, we observe whether or not there is a school in a parish and whether or not the school offers all nine compulsory school grades (1^{st} to 9^{th}) or, alternatively, was a feeder school offering grades 1-6 (or the like).[9] Lastly, grocery stores

[7] A common approach to measure job access is to use commuting zones, e.g., Autor and Dorn (2009) who use the commuting zones developed by Tolbert and Sizer (1996). Commuting zones have the advantage over other geographic units used for analysis of local labor markets that they are are defined across state or other administrative boundaries. However, our extremely detailed time-to-commute computations appear even more exact and are not subject to any choice of border between commuting zones.

[8] This information does not appear in the registries but was found in annual publications from the Danish Health Authorities 1992-2022, e.g., Sundhedsstyrelsen (1989). The parish was found using www.sogn.dk. We measure ER units that are 24H open.

[9] A "feeder school" is a school that has students from grade 1 but not all the way up to the end of compulsory school. The students are therefore "fed" into another school. In Denmark, most feeder schools offer up to 5^{th}, 6^{th} or 7^{th} grade, but it can also be up to 3^{rd} or 8^{th} grade. In our model, we treat all feeder schools alike. The information on feeder schools is available in the registries from the school year since 2007/2008 only. For earlier years the information was found in annual publications of the Danish handbook of schools (In Danish: Den Danske Skolehåndbog) combined with information from the Government Agency for IT & Learning (www.stil.dk). Feeder schools are usually found in rural

are observed through the VAT payments made by companies. For this paper, the interest is mainly in whether there is a supermarket, mini-market, or the like as an indicator of the availability of the most basic daily life needs.[10]

2.3 Empirical facts

In the introduction, it was noted how countries around the globe have seen declining rural populations. Denmark is no exception. In 1999, the rural Danish population constituted 23% of the total population, while this share had decreased to 18% of the population in 2022.[11]

The demographic development whereby the number of newborn has decreased combined with the maintained trend towards further urbanization has resulted in the closure of many public schools – especially in rural areas. In addition, a reform that amalgamated municipalities was implemented in 2007, see Blom-Hansen et al. (2016) for details, and following the municipal reform, a new law concerning local governments' annual fiscal budgets was implemented in 2011. According to this law, municipalities would be economically sanctioned if they overran their annual fiscal budget. Subsequently, 8 percent of all public schools in Denmark were closed between 2010 and 2012, see Figure 1, and most of these schools were feeder schools in rural neighborhoods.[12]

From 1992-2022, 60% of all 24-hour-open emergency room units were closed in Denmark, see Figure 2, top panel. This resulted in a marked increase in the travel time

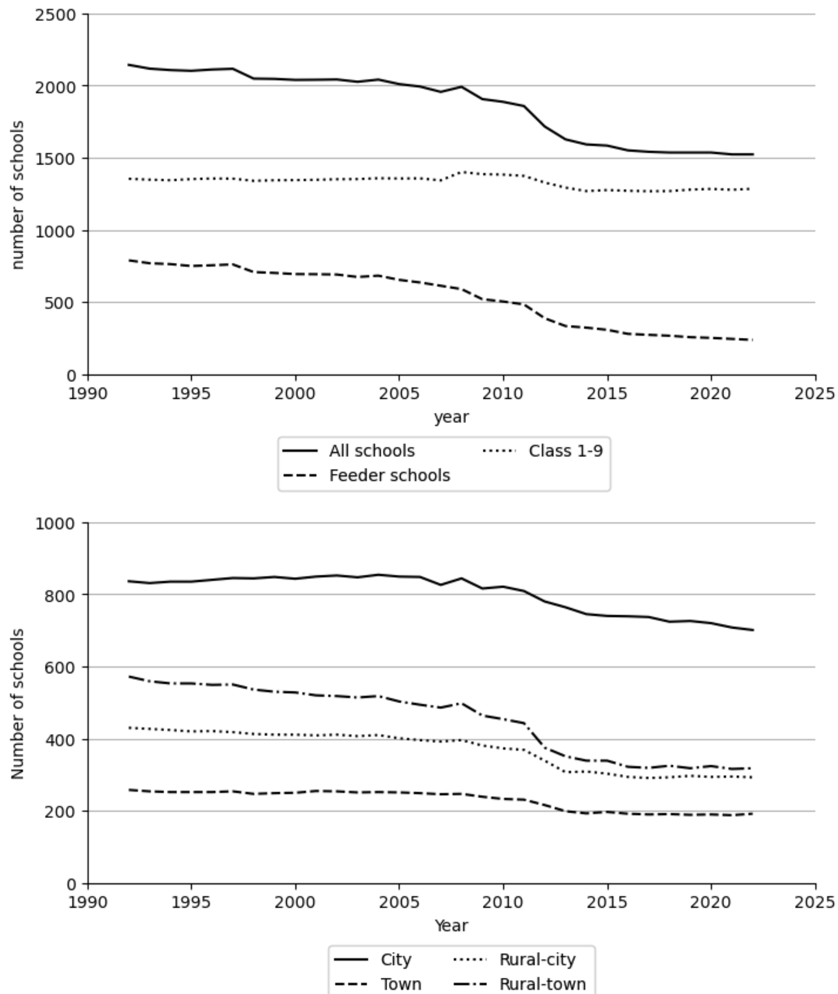
areas.

[10]See appendix B for details.

[11]In absolute numbers, the rural population declined by 240,000 persons equivalent to 18.1% from 1999 to 2022. During the same years, the entire population of Denmark increased by 2.0%. Source: Annual publications of "byopgørelsen" 1999-2017 and subsequently, for 2018-2022, the "by2" table from Statistics Denmark.

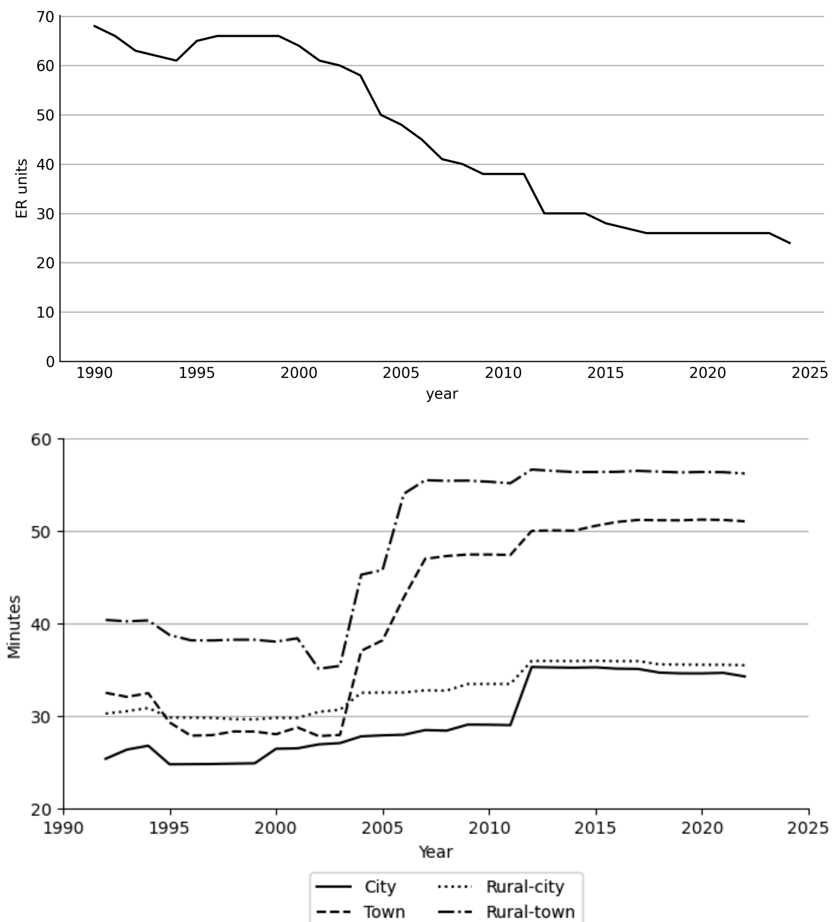
[12]Hvidman et al. (2026) study the effects of this reform and find that the incentives reduced government spending – even to a higher degree than necessary. This "overshooting" meant that municipalities reduced spending more than intended due to uncertainty about their ability to meet budget targets and avoid economic sanctions.

Figure 1: Schools in Denmark, 1992-2022



Note: *Upper*: The Number of Schools in Denmark, by feeder school and 1^{st}-9^{th} grade. *Lower*: The Number of Schools in Denmark, by type of parish. *Sources*: For the years prior to 2007, The Danish handbook of schools (In Danish: Den Danske Skolehåndbog) combined with information from the Government Agency for IT & Learning (www.stil.dk). Since 2007: The Institution registry.

Figure 2: Number of ER units and travel time, 1992-2022



Note: *Upper*: Number of 24H-Opened ER units in Denmark, 1990-2024. *Lower*: Distance to Nearest Emergency Unit, minutes travel time by car. *Source*: Sundhedsstyrelsen (1989) and subsequent annual publications, and own calculations.

distance to nearest ER unit. For people living in rural parishes away from cities, the average travel time distance to nearest ER unit was 42 minutes in 1992 (24 minutes for people living in urban, city neighborhoods) and rose to 55 minutes in 2022 (34 minutes for people living in urban, city neighborhoods), see Figure 2, bottom panel.

Also of importance to this paper is the geographical dispersion in the access and change in access to jobs across parishes. Computing the change between 1992 and 2022 in the number of jobs within a one-hour commute, we find that, generally, the number of white-collar jobs has risen over these years (Figure 3, upper panel) while the number of blue-collar jobs has fallen in rural Denmark and risen in neighborhoods within a one-hour commute from Copenhagen or Aarhus (Figure 3, lower panel).[13] The rise in the number of white-collar jobs is much higher in parishes within a one-hour commute from the major cities.

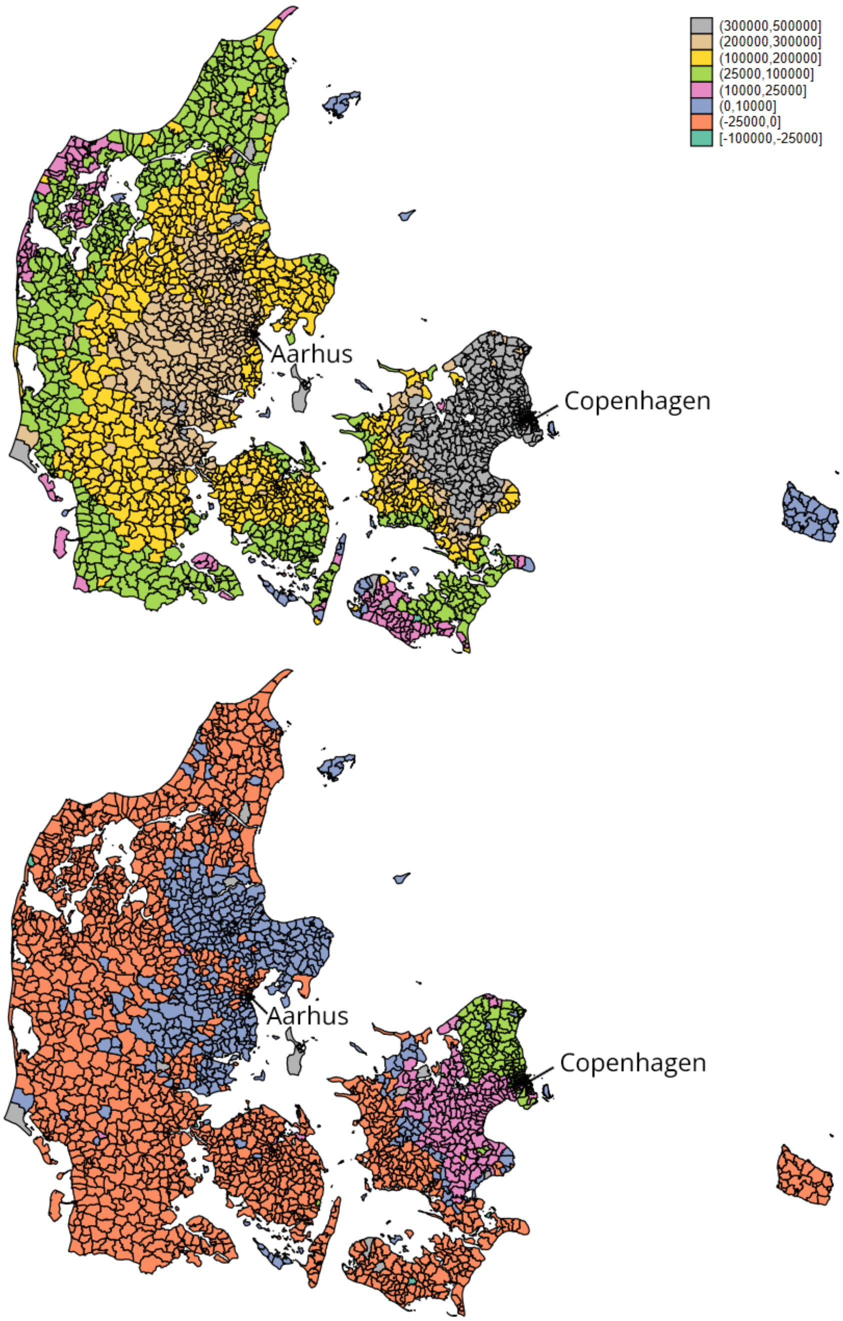
Another element of rural decline is the accelerated aging of the rural populations. The old-age dependency ratio, i.e. the number of over-65-year-olds over the number of 16-64-year-olds increased greatly from the early 1990s to 2022, see Figure 4. The increase occurred across all neighborhood types –urban as well as rural– although it was much stronger in rural neighborhoods (towns and rural-towns), where it doubled. The mirror image of the increasing old-age dependency ratio is the decrease in the share of families with children.[14] The share of families with children has decreased from about 27% in the early 1990s to about 20% in rural neighborhoods far from major towns or cities, while the share of child families has remained largely constant at around 25% in city neighborhoods.

Lastly, Figure 5 shows the development in local grocery stores across types of neighborhoods. Clear from Figure 5, the share of neighborhoods with grocery store decreased substantially in the two rural types of neighborhood while it remained constant at a high level (about 90%) in city and town neighborhoods. The drop in the share of neighborhoods with grocery stores from about 50% to below 40% in rural neighborhoods constitutes more than a 20% decrease, and occurred primarily between the year 2000 and 2015.

[13]Copenhagen is the capital (population approximately 700,000) while Aarhus is the second largest city in Denmark (population approximately 300,000). Both with large adjacent catchment areas.

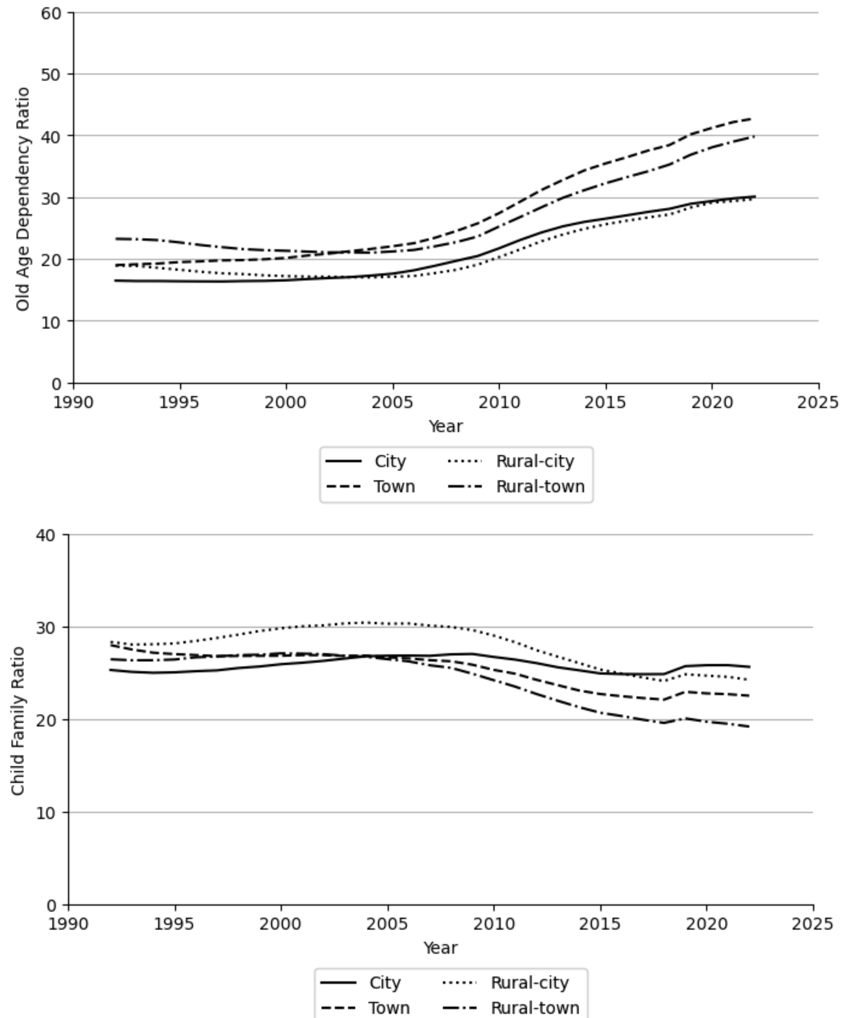
[14]"Child family" is defined as families with a child aged 0-14. This choice is made since children / adolescents aged 15+ better can travel longer distances to attend school / high school. The value of a local school therefore links more strongly to younger children.

Figure 3: Change in access to white-collar and blue-collar jobs within 1-hour commute, by neighborhood 1992-2022



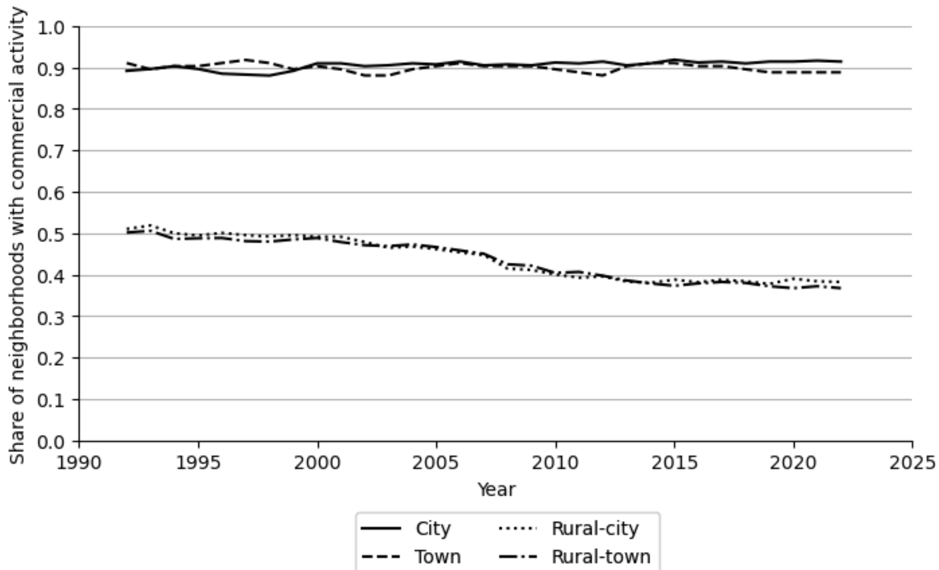
Note: *Top panel*: Change in the number of white-collar jobs accessible within a one-hour commute. *Lower panel*: Change in the number of blue-collar jobs accessible within a one-hour commute. Each cell is a neighborhood. Computations based on a neighborhood distance matrix linked to administrative records, which makes it possible to compute the number of jobs within a one-hour commute by car across levels of education. White-collar jobs are here defined as jobs among individuals who have completed a college or university degree. Blue-collar jobs are defined as jobs held by individuals with a qualifying vocational degree or with no qualifying degree.

Figure 4: Old-age dependency ratio and share of families with children 1992-2022, by type of parish



Note: *Upper*: Old-age dependency ratio is defined as the share of the population aged 65+ over the share of the population aged 16-64. *Lower*: Share of families with children (families with a child 0-14 years of age).

Figure 5: Grocery store in the neighborhood



Note: Share of neighborhoods with a grocery store as defined in appendix C.

3 The model

We adapt a model structure that resembles Bayer et al. (2016), and follow persons in households from the first time they choose to become a home owner. In each period, the household decides where to live. The choice of where to live is inherently dynamic, as moving costs make it prohibitively expensive to move every period, and this induces forward-looking behavior in order to optimize over the life cycle. If a household decides to move, it also has to choose where to move. These decisions are captured in the same control variable $d_{i,t} = j \epsilon \{0, 1, ..., J\}$, where j indexes the neighborhoods, J denotes the total number of neighborhoods and 0 is the outside option. A decision to stay is captured by $d_{i,t} = J + 1$.

The model consists of two sets of state variables; one set that characterizes the neighborhood ($X_{j,t}$) and another that characterizes the household ($Z_{i,t}$), where i indexes the households, and t indexes time periods. Let $h_{i,t} \epsilon \{0, 1, ..., J\}$ denote the neighborhood chosen in period $t-1$, including the outside option. In addition to these observable state variables, the model also includes unobservable neighborhood characteristics, $\xi_{j,t}$, and an idiosyncratic shock to the flow utility associated with households and neighborhoods, $\varepsilon_{i,j,t}$. Let the set $s_{i_t} = \{z_{i,t}, x_t, \xi_t, d_{i,t-1}, z_{i,t-1}, x_{t-1}, \xi_{t-1}, d_{i,t-2}, ...\}$ contain all relevant information in order for the household to predict the future characteristics of the household and neighborhoods.

The moving decision is made repeatedly every period giving rise to an infinite horizon model. The Bellman equation for the household therefore becomes

$$V(s_{i,t}, \varepsilon_{i,t}) = \max_j \{u_{i,j,t} + \beta E\left[V(s_{i,t+1}, \varepsilon_{i,t+1} | s_{i,t}, \varepsilon_{i,t})\right]\}$$

Under regularity conditions given by Rust (1987) this becomes a contraction mapping.

3.1 Identification

In line with most work on dynamic discrete choice models, identification here rests in part on assumptions about rational expectations, expected utility maximization, conditional independence, and additive and time-separable preferences, see Rust (1994).

These assumptions are not enough to establish any forward-looking behavior, see Rust (1994), Magnac and Thesmar (2002), and Rust (2014). The intuition is that if state variables impact the instantaneous utility and expected future utility alike, we need exogenous variation that shifts expectations but not current-period utility in order to establish forward-looking behavior. In our case, exogenous variation arises from time-variation in all the neighborhood state variables, $X_{j,t}$.

It is important for the dynamics of the model whether any change in a state variable over time is mean-reverting or persistent. Lagged neighborhood characteristics, i.e., local service levels and amenities, are informative for households when they form expectations about the future utility associated with a given neighborhood. Based on a static model, the disutility of, say, a school closure will likely be downward biased. The intuition is that a household observes a parish with no school and expects this to prevail in the future. In a dynamic model, the households observe the change from having a local school to no school, and incorporate this change in their expectations of future (lower) house prices in this neighborhood. This will reduce their willingness-to-pay in a dynamic model, while a naïve static approach only would consider the instantaneous current period disutility of having no school in the neighborhood. In our model, these dynamics are even more important if a recent school closure signals future closure of commercial activity (here measured as the occurrence of a local grocery store) and an accelerated further decline in local house prices. The characteristics of our neighborhoods (school, distance to ER unit, job market access and grocery store) can arguably be considered persistent attributes of the neighborhood.[15] In addition, a static modeling approach would also miss that the composition of the likely changes in the neighborhood. As a result of lower house prices, different households (likely older and/or single) would favor this neighborhood.

4 Estimation

The intuition behind the estimation procedure is to first establish whether the household moves or not, to outline how the moving costs are computed, and to determine how households choose the neighborhood that maximizes utility over the lifetime. In turn, we characterize how households form their expectations and recover per-period utility across all neighborhoods and over time.

[15]The bias arising from a static model would have the opposite sign if the change in neighborhood characteristics would be temporary (mean-reverting). The sign of the bias of course depends on whether the neighborhood characteristics are considered positive or negative. Examples of negative characteristics are air pollution and crime (none of which are included in this model).

In a dynamic model of residential sorting, moving costs play an important role. The households optimize life cycle utility by choosing where to live in each period, which, given Markovian transition probabilities, is a function of the state variables only, i.e. $d_{i,t} = d^*_{i,t}(s_{i,t}, \epsilon_{i,t})$, where "*" signifies the optimal decision rule.

4.1 Move or stay?

Assume that a household moves. Conditional on moving, the household will incur a moving cost. Moving costs (MC) include financial moving costs (FMC) in terms of a realtor fee, and psychological moving costs (PMC) that may depend on household characteristics. The financial moving costs are assumed to constitute 4% of the house value.[16] This provides a link between utility and a pecuniary value, which enables us to compute willingness-to-pay of other characteristics that enter the utility function. Given that the $FMCs$ are a function of the housing value in the current neighborhood only, it is constant for all possible future neighborhoods and conditional on moving. The moving costs therefore drop out of the decision. The choice-specific value function can therefore be written as

$$\nu_j^{MC}(s_{i,t}, h_{i_t}) = \nu\left(s_{i,t}\right) - MC\left(Z_{i,t}, X_{h_{i_t}}\right) * \mathbb{1}\left(move = 1\right)$$

and conditional on moving, households maximize the expected lifetime utility of $\nu\left(s_{i,t}\right)$. The model is estimated for types of households, τ, which are discretized values of household characteristics.[17] The mean lifetime utilities, ν_t^τ, are only defined up to a constant and some form of normalization is therefore required. With no loss of generality, we set the normalization constant (m_t^τ) such that the expected lifetime utility for each type-year combination has mean zero. We thus estimate $\tilde{\nu}_{j,t}^\tau = \nu_{j,t}^\tau - m_t^\tau$. Conditional upon moving, household i of type τ chooses the neighborhood j where $\tilde{\nu}_{j,t}^\tau + \epsilon_{i,j,t} > \tilde{\nu}_{k,t}^\tau$

[16] Measured as the average house price in neighborhood j in period t.

[17] We discretize wealth into 10 groups. The remaining household characteristics are all binary (old, child family, education). Multiplying these we get $10 \times 2 \times 2 \times 2 = 80$ different types, τ.

$+ \epsilon_{i,k,t} \; \forall \; k \neq j$. As we assume that $\epsilon_{i,j,t}$ are i.i.d. distributed errors of Type I Extreme Value, the probability of any household of type $\overline{\tau}$ moving to neighborhood j can be written as $P^{\overline{\tau}}_{j,t} = \frac{exp\left(\tilde{\nu}^{\overline{\tau}}_{j,t}\right)}{\sum_{k=1}^{J} exp\left(\tilde{\nu}^{\overline{\tau}}_{j,t}\right)}$ conditional on moving to an inside option. Similarly, moving to the outside option can be written as $P^{\overline{\tau}}_{0,t} = \frac{exp\left(\tilde{\nu}^{\overline{\tau}}_{0,t}\right)}{\sum_{k=0}^{J} exp\left(\tilde{\nu}^{\overline{\tau}}_{j,t}\right)}$, and the combined probability therefore becomes $P^{\overline{\tau}}_{j,t} = \left(1 - P^{\overline{\tau}}_{0,t}\right) \times P^{\overline{\tau}}_{j,t}$.

Whether the household decides to move depends on whether the utility from staying, net of moving costs, is lower than the maximum utility from moving. The moving costs imply a decrease in wealth and therefore an endogenous shift in type from τ to $\overline{\tau}$. A household of type τ will choose to stay if $\nu^{\tau}_{J+1} + \epsilon_{i,J+1,t} > \underset{k}{max}\left[\tilde{\nu}^{\tau}_{k,t} + \epsilon_{i,k,t}\right] - PMC^{\overline{\tau}}$. Recall that $\tilde{\nu}^{\tau}_{j} = \nu^{\tau}_{j} - m^{\tau}$, which means that we can write the stay decision rule as $\tilde{\nu}^{\tau}_{J+1} + \epsilon_{i,J+1,t} > \underset{k}{max}\left[\tilde{\nu}^{\tau}_{k,t} + \epsilon_{i,k,t}\right] - (m^{\tau}_{t} - m^{\overline{\tau}}_{t}) - PMC^{\overline{\tau}}$, where $(m^{\tau}_{t} - m^{\overline{\tau}}_{t})$ is unobserved.[18]

4.2 Expectations and transitions

The value functions depend on future-state variables for which households need to form expectations based on current-state variables.

The only endogenous-state variable in the model is wealth, which changes inside the model when a household chooses to move and therefore incurs a moving cost (and changes type from τ to $\overline{\tau}$). In addition, households also need to form expectations about their future type transitions. For example, a young couple may expect to become a family with children, and a middle-aged couple may expect to turn "old". Since moving costs are assumed to be a function of house prices, households also need to form expectations about how house prices will transition in the future in order to form expectations about their life trajectory.

Importantly, for our model, house price expectations (named $hprice_{j,t}$ below) depend

[18] Following Bayer et al. (2016) we parameterize this unobserved difference so that $\left(m^{\tau}_{t} - m^{\overline{\tau}}_{t}\right) = FMC_{i,t} \times \gamma^{\overline{\tau}_{fmc}}$ where $FMC_{i,t} = 0.04 \times price_{h_{i,t}}$ and $\gamma^{\overline{\tau}_{fmc}} = \overline{Z'_{i,t}} \times \gamma_{fmc}$.

on neighborhood characteristics and changes in neighborhood characteristics over time. This is important because it captures the dynamics we are mostly interested in and provides the variation that identify key parameters of interest, as shown below,

$$hprice_{j,t} = \gamma_{0,j} + \sum_{l=0}^{L} \tilde{X}'_{j,t-l}\gamma_{2,t-l} + \sum_{l=0}^{L} hprice_{j,t-l}\gamma_{3,t-l} + \gamma_{4,j}t + \varrho^{\tau}_{j,t},$$

where $\tilde{X}$ includes the characteristics in X of the neighborhood that vary over time. In addition, $\tilde{X}$ also includes indicators for *changes* in neighborhood state variables, i.e. an indicator for whether or not there is a school in the parish, changes between period t and period $t-l$ interacted with some of the other current-period state variables, $commercial_{j,t}$ and the average house prices in each parish, $price_{j,t}$.

If a school closes within the last L periods ($L = 2$), this may signal further local decline and the expected future drop in house prices above and beyond the drop in house prices in the current period, which will alter the utility in the current period. Obviously, a new school may also be opened, giving the possibility of positive dynamic transitions.

Transitions of the choice-specific value functions, $\nu^{\tau}_{j,t}$, follow the following equation:

$$\nu^{\tau}_{j,t} = \rho^{\tau}_{0,j} + \sum_{l=1}^{L} \tilde{X}'_{j,t-l}\rho_{2,t-l} + \sum_{t=0}^{L} hprice_{j,t-l}\rho_{3,t-l} + \rho_{4,j}t + \varrho^{\tau}_{j,t}$$

Mean flow utilities can now be computed for each type, period, and neighborhood:

$$u^{\tau}_{j,t} = \nu^{\tau}_{j,t} - \beta E\left[log\left((exp(\nu^{\tau_{t+1}}_{J+1,t+1}) + \sum_{k=0}^{J} exp\left(\nu^{\overline{\tau}_{t+1}}_{k,t+1} - PMC^{\overline{\tau}_{t+1}}\right)\right) | s_{i,t}, d_{i,t} = j\right],$$

where we plug in the values obtained through all the above-mentioned steps, and where β is set to 0.95.

4.3 Willingness to pay

The welfare and willingness-to-pay measures are obtained by comparing households' indirect expected utilities across counterfactual scenarios and scaling these differences by the marginal utility of income, following the approach in, e.g., Bayer et al. (2009) and Bayer et al. (2016).

Given the per-period flow utilities, by using a simple linear fixed effects regression we can estimate how they depend on neighborhood characteristics. We estimate

$u^{\tau}_{j,t} = \alpha^{\tau}_0 + \alpha^{\tau}_r + \alpha^{\tau}_t + X'_{j,t}\alpha^{\tau}_x + \xi^{\tau}_{j,t}$,

where we include fixed effects for region (r), type(τ), and year (t). This provides a decomposition of per-period utility.

In order to measure per-period utilities in pecuniary terms we compute the user cost of owning a home. This is typically computed as a percentage of the home value and we here follow Bayer et al. (2016) and calculate the user cost as 5 percent of mean prices in the neighborhood. User costs are clearly endogenous since price is an equilibrium outcome that reflects unobserved neighborhood attributes (e.g., unobserved school quality, amenities), and any regressor built directly from price will therefore be correlated with those unobservables. Identification stems from the assumption that the marginal value of wealth on lifetime utility is the same as the marginal value of user costs, and hence given by γ^{τ}_{fmc}.[19]

Let $\tilde{X}$ denote the non-user cost components of X, then we can get $u^{\tau}_{j,t} + \widehat{\gamma^{\tau}_{fmc}}\, usercost_{j,t}$ $= \alpha^{\tau}_0 + \alpha^{\tau}_r + \alpha^{\tau}_t + \tilde{X}'_{j,t}\alpha^{\tau}_x + \xi^{\tau}_{j,t}$.

The equation above can be computed when we constrain the the fixed effects to be the same over τ, but one could also allow them to vary.

Amenity-specific willingness to pay for neighborhood characteristics can now be computed as

$$\text{WtP}^{\tau} = \frac{\alpha^{\tau}_x}{\gamma^{\tau}_{fmc}}.$$

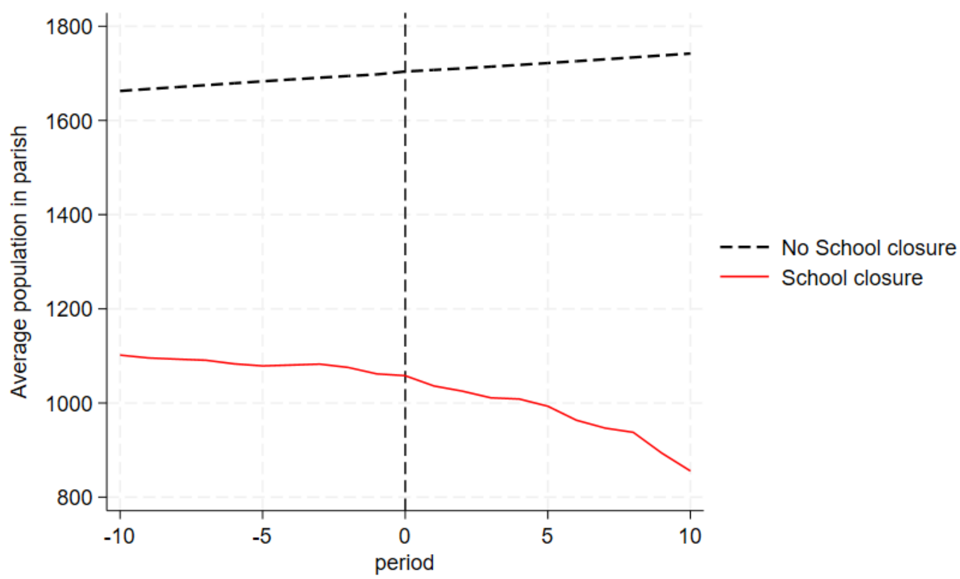
[19] γ^{τ}_{fmc} was discussed in footnote 17.

5 Results

5.1 Difference-in-difference descriptives

We have argued above for the need to estimate a dynamic model in order to better understand residential sorting over time and events such as school closures. Imagine a Differences-in-Differences (DiD) reduced form approach to the analysis of changes in the population as a school is closed.

Figure 6: Average population size in neighborhood conditional on school closure or no school closure



Note: Average population size by school closure, stacked at the time of school closure. The y axis shows the average population size in parishes that have experienced school closures and parishes that have not. The x axis is calculated in periods corresponding to one year, which is seen here in relation to the time of school closure. In the rare event of more than one school in a parish, it is only the last school closure that counts (going from one or more schools in parish to no school).

The raw data, averaged over school closure / no school closure are shown in Figure 6. The overall population size of Denmark has grown from 1992 to 2022, but the population size in parishes that experienced a school closure had declining population sizes when considering the ten years before and after the school closure.[20]

As is clear from Figure 6, the parallel trend assumption underlying the DiD approach does not hold. The average population size declines slightly before the school closes but seemingly more after (periods 1-10) with the steepest gradient from period 8.[21] This underscores the need for a dynamic approach to analyzing the development in services and amenities over time.

5.2 Parameter estimates and WtP for amenities

Parameter estimates

The parameter estimates from the mean per-period flow utilities regressed on fixed effects and neighborhood characteristics yield the parameter estimates given in Table 1.

Each parameter estimate needs to be considered in terms of its unit of measurement. With respect to schools (feeder school and school 1-9), the variable is an indicator for whether the school is in the neighborhood. Both types of school enter with a positive and highly statistically significant estimate. Not surprisingly, having classes 1-9 is valued higher than having a feeder school (simply seen by the higher parameter estimate for school 1-9). Grocery store is also simply an indicator for whether the neighborhood has a grocery store or not. The parameter estimate here is even higher than for the schools and also highly significant.

Workplaces and ER distance are measured on a continuous scale. Workplaces are measured in units of 1,000 workplaces accessible by a one-hour commute by car. Both the access to jobs for college/university-educated individuals (including short-term colleges of up to two years) and access to jobs for unskilled and skilled workers is positively valued

[20] The population size of Denmark was 5,162,000 persons in 1992 and had grown to 5,873,000 persons by the end of 2022. Source: https://danmarkshistorien.lex.dk/Danmarks$_{b}efolkningsudvikling_{1}769-2021$.

[21] This corroborates findings by Sørensen et al. (2021), who analyze school closures in Tønder municipality (Denmark).

Table 1: Baseline parameter estimates

	(1) Param. Est.
Feeder school	0.0315***
	(0.0050)
School 1-9	0.0544***
	(0.0058)
N workplaces coll/uni educated	0.0037***
	(0.00037)
N workplaces unskilled/skilled	0.0066***
	(0.00220)
Grocery store	0.0828***
	(0.0036)
ER distance	0.0001
	(0.0001)

Note: Feeder school and School 1-9 are indicator variables. N workplaces are measured in 1,000s. Grocery store is an indicator, and ER distance is measured in minutes by car. Standard errors in parentheses. The model includes year and parish fixed effects. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

and highly significant, but the change in ER units (measured in minutes) does not appear as statistically significant, and the point estimate is essentially zero.

Willingness to pay

The approach to computing willingness to pay follows the decomposition of per-period utilities as outlined above. This yields per-period WtPs. It is not clear exactly how such per-period WtPs translate into a net present value computation. A simple approach which we adhere to here is to compute a perpetuity $PV = \frac{per-periodWtP's}{r}$.[22] The results from these computations are found in column (2) of Table 2.

[22] Transitioning from a fixed periodic payment to an infinite stream of payments (a perpetuity) simplifies your net present value calculation. Rather than discounting infinite individual periods, you collapse the infinite geometric series into one simple limit formula.

Table 2: Willingness to Pay and NVP computations (USD)

	(1) WtP	(2) NPV(WtP)
Feeder school	1,764	29,401
School 1-9	3,046	50,775
N workplaces coll/uni educated	209	3,486
N workplaces unskilled/skilled	369	6,153
Grocery store	4,637	77,282
ER distance	NA	NA

Note: Feeder school and School 1-9 are indicator variables. N workplaces are measured in 1,000s. Grocery store is an indicator. ER distance is not included since the baseline parameter estimates are insignificant. Interest rate = 6%.

The per-period WtP for having a feeder school in the neighborhood is found to be USD 1,764 , and assuming an interest rate of 6%, the perpetuity becomes USD 29,401, while having a school 1-9 in the neighborhood yields a perpetuity of USD 50,775. These amounts appear reasonable given that we expect schools to be an important characteristic for future households to move to the neighborhood, and given the dynamic consequences if that ceases to happen.

Similarly, 1,000 workplaces currently held by college/university-educated individuals is valued at a net present value of USD 3,486, while 1,000 workplaces currently held by unskilled/skilled has a net present value of USD 6,153. In part, this may reflect that there has been a rise in the number of white-collar jobs and a decline in the number of blue-collar jobs.

Lastly, the per-period willingness to pay for a grocery store is found to be USD 4,637, which translates into a net present value of USD 77,282. While the value for the other amenities may appear reasonable, this NPV appears very high indeed and future research should bring additional information about the drivers behind such a high estimate. Ceteris paribus, the estimate for the valuation of a grocery store underscores its importance for everyday life across all stages of life (family with children, old age pensioner, etc.).

A possible extension here is to not compute the simple perpetuities, but instead think of year intervals where certain characteristics are in high value and link the valuations more to household-type characteristics. For instance, one could assume that households hold expectation to their future types and keep such expectation in mind when they purchase their home. Another relevant extension would be to compute willingness to pay across neighborhood types.[23]

6 Discussion and conclusion

This paper is the first to make a comprehensive assessment of important neighborhood characteristics of rural neighborhoods in a nationwide analysis using panel data from a 31-year period. While the model setup and estimation strategy follows Bayer et al. (2016), there are nevertheless major differences. An important difference that sets our paper apart from all existing studies, including Bayer et al. (2016), is that our model and data cover the entire nation, allowing us to focus on rural areas and very different neighborhood characteristics compared to existing analyses of metropolitan areas.

The administrative registry data supplemented by a collection of additional local information makes our study's data quite exceptional. The 31 years of panel data of all homeowner sales and purchases, together with detailed annual individual seller and buyer

[23]This has been done for rural-town neighborhoods but turned out insignificantly different from the overall average. This is surprising even though we include neighborhood fixed effects, which purge a lot of variation in data.

characteristics, make it possible to better understand the dynamics over time. For example, the impact on residential sorting that follows a school closure likely manifests itself over many years rather than immediately. Lastly, an important strength of this study is the high degree of events, such as changes in access to local school and grocery stores, as well as changes over time in distances to ER units, and job access within a one-hour commute. As a further addition to the literature, this paper utilizes the development of a parish-by-parish distance matrix, which offers new and improved possibilities for analysis of local labor markets.

A key issue for our model estimates is the threat of missing other relevant amenities, i.e., if there are amenities that are correlated with the current set and are important for moving patterns, then current amenities are going to pick up the values of these missing amenities in the manner of a hedonic regression.[24] Even though the WtPs are estimated using neighborhood fixed effects, time variation in other amenities may be of importance – which indicates the importance of assessing the model fit by using event study out-of-sample analysis (as explained below).

The focus here is on the neighborhoods and how types of households respond to services and amenities. Clearly, a model that emphasized household life-cycle moving patterns and home-owner market equilibrium would be of further interest.

6.1 Relevant extensions

Dynamics

A key feature that justifies the use of the underlying relatively advanced model setup is the importance of *dynamics*. While it is relatively straightforward to contemplate further dynamic extensions, it is usually quite laborious to actually implement such extensions.

[24]Missing amenities as could be school quality, childcare/elderly care, proximity to cultural offers, or crime, to name but a few.

Nevertheless, it would be interesting (and a natural next step) to endogenize one or more of the currently exogenous-state variables. In particular, one could envisage that the prevalence of a grocery store would be a function of the existence of a school, such that a school closure would signal future closure of the local grocery store. If such effects are any more than hearsay and speculation, they would underscore the importance of school closures and reinforce the need for better decision-making material.

In Figure 7, we show an extended version of Figure 6 in which the share of neighborhoods with a grocery store is shown according to the timing of school closures. The figure reveals that the school closure *maybe* causes grocery store closure in Rural-City neighborhoods (upper-right corner), where we see a decrease in grocery stores *after* the school closure. However, a similar pattern is largely absent in the other three quadrants, where, if anything, it appears that the causal impact may run from grocery store to school closure.[25]

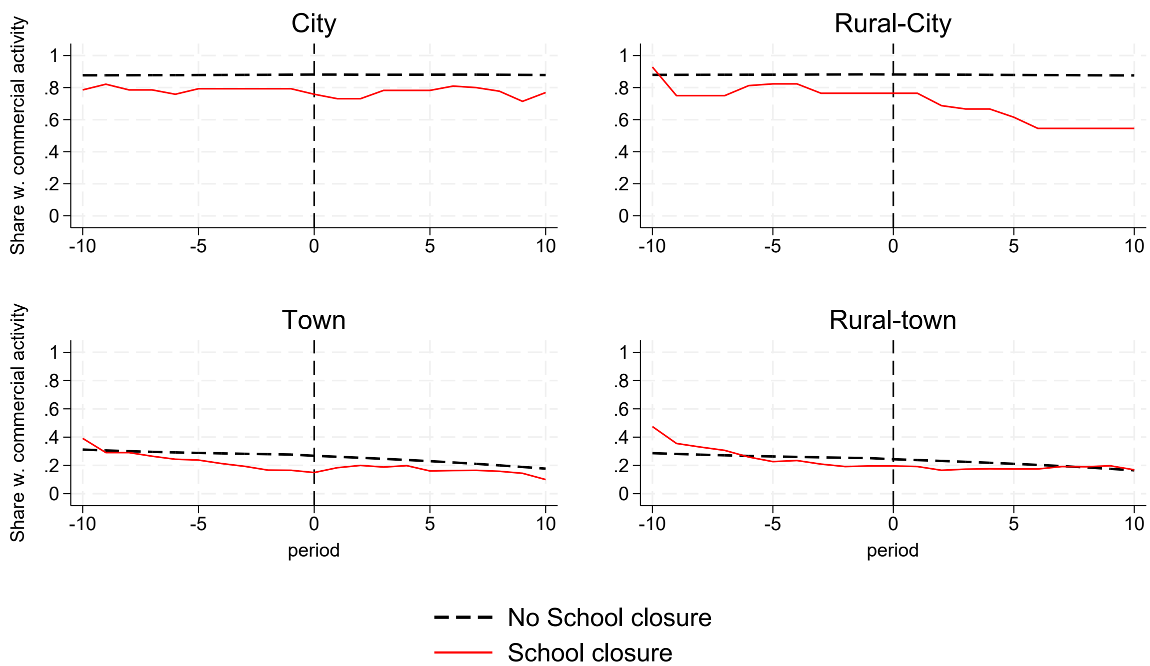
Out-of-sample model fit

Another extension we may think of is to make an out-of-sample prediction to test the model parameters in the vein of Todd and Wolpin (2006).[26] While local characteristics change across geographic units there are no geographical parameters in the model per se (e.g., the model does not allow for separate parameters for the west coast), and we may therefore make an out-of-sample prediction by leaving out all neighborhoods on the island of Funen (the island in the middle of Denmark where about 10% of the population lives), estimating the model parameters on the remaining 90% sample, and using the model pa-

[25] We previously argued that DiD likely is ill-suited for estimation here since a pre-trend assumption is unlikely to hold. Figure 7 should therefore only be seen as suggestive, not causal, evidence. An important underlying mechanism could be that the financial crisis starting in 2008 caused grocery store closures and the municipal reform and subsequent first election afterwards, in 2010, was catalyst for school closures. This underscores the complexity and difficulty in identifying the impact of changes in amenities - even in a dynamic model with exogenous changes such as school closures.

[26] Todd and Wolpin (2006) use data from a randomized social experiment in Mexico to estimate and validate a dynamic behavioral model of parental decisions about fertility and child schooling.

Figure 7: Share of parish type with grocery store, by school closure



Note: Average share of neighborhoods with a grocery store, stacked at the time of school closure. The y-axis shows the average share of neighborhoods with a grocery store in parishes (neighborhoods) that have experienced school closures and parishes that have not. The x-axis is calculated in periods corresponding to one year, which is seen here in relation to the time of school closure. In the rare event of more than one school in a parish, it is only the last school closure that counts (going from one or more schools in parish to no school).

rameters to predict the change in population from school closures on Funen. This would in effect be an event study out-of-sample prediction that would make a strong case for the model (if proven successful).

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Supplementary Material for

Rural Decline and Residential Sorting

Nicolai Kristensen (2026)

A Appendix: More on the estimation of the model

An individual chooses action $d_t \epsilon \mathbf{D}_t$ for $t = 1, ...T$. The individual's objective is to choose the alternative that maximizes the net present value of future utility. The individual utility is normalized such that $U(S_t \mid d = =0$.

$$EV_{t+1}(S_{t+1}) = \int \int \max_{d \ \epsilon \ \mathbf{D}} \{V_{t+1}(d), d \ \ \epsilon \ \mathbf{D}\} \, dG(\varepsilon^w) dH(\varepsilon^{np})$$

We use standard results from dynamic discrete-choice models, albeit perhaps not immediately transparently. First, when moving from the Bellman equation to the closed-form expression for the value function, the key step is the assumption that the idiosyncratic taste shocks are i.i.d. extreme values; this implies that the expected maximum over alternatives can be written as a smooth âlog sumâ term, as shown for example in Rust (1987) and Kennan and Walker (2011).

The choice probabilities take the familiar multinomial logit form because the difference of two i.i.d. type I extreme value variables is logit distributed; this yields the exponential utility index divided by the sum of exponentials over all neighborhoods, as in Bayer et al. (2004) and Bayer et al. (2016). Finally, the welfare and willingness-to-pay expressions follow from the envelope theorem in this logit setting: differences in expected value functions can be scaled by the marginal utility of income to obtain compensating variation measures, see, for instance, Bayer et al. (2009).

B Appendix: Data details

The estate data originate from five different registries[27], and include detailed information on all houses as well as any land property connected to the dwelling. All owner-occupied

[27] The Dwelling Registry; The Estate Sales Registry; The Estate Value Assessment Registry; The Owner of Estate (House/Apartment); Estate Tax Registry

houses are given an assessed value for each year. These assessments, made for tax purposes, are relatively close to actual selling prices, but do tend to underestimate them slightly. Hence, we adjust the assessed prices with the percentage deviance between assessed and actual selling price among the houses sold locally that year.

C Definitions of the X and Z variables

Variable	Description
X = neighborhood characteristics	
School	$1^{st} - 9^{th}$ grade school in neighborhood; feeder school in neighborhood; no school in neighborhood.
Job access	Number of jobs within 1 hour commute by car, split by jobs at basic level and more qualified jobs.
ER unit	Travel time in car to nearest 24 open emergency unit. Varies over time and neighborhood.
Commercial	Indicator =1 if supermarket, kiosk or similar exists in neighborhood, and =0 otherwise (exact definition below).
Unskilled includes high school	
Z = household characteristics	
Education	Skilled/unskilled and college/university.
Old	Indicator =1 if oldest person in household is aged 65+ and =0 otherwise.
Child family	Indicator =1 if at least one child in family is aged below 15, and =0 otherwise.
Wealth	Wealth is split into deciles computed by year.

C.1 Neighborhoods

The neighborhoods here are defined as parishes, and these belong to one can be are divided into one of five categories defined as follows.

1. **Cities**. City or town areas in or close to the biggest cities. Areas where at least half of the population lives in (a) a city or town with more than 3,000 inhabitants and (b) within a half-hour drive from one of the major city areas in the country.[28]

2. **Towns**. City or town areas further away from the biggest cities. Areas where at least half of the population lives in (a) a city or town with more than 3,000 inhabitants and (b) not within a half-hour drive from one of the major city areas in the country.

3. **Rural cities**. Rural district close to the biggest cities. Areas where more than half of the population lives (a) outside a city or town with more than 3,000 inhabitants and (b) within a half-hour drive from one of the major city areas in the country.

4. **Rural towns**. Rural district further away from the biggest cities. Areas where more than half of the population lives (a) outside a city or town with more than 3,000 inhabitants and (b) not within a half-hour drive from one of the major city areas in the country.

5. **Small islands**. There are only few observations in this category, and, as they face rather different circumstances. We therefore exclude them from the model.

As mentioned, even if the parish code changes between 2014 and later (or earlier) years, unique dwelling numbers makes it possible to uphold the 2014 parish definition.

[28]The major city areas are here defined as the greater metropolitan area of Copenhagen and the 11 biggest city areas outside of Copenhagen: Aarhus, Odense, Aalborg, Esbjerg, Randers, Kolding, Horsens, Vejle, Roskilde, Herning og Elsinore.

A minor measurement error may occur for new dwellings built in a parish which did not exist in 2014. In this case we know the dwelling number and the new parish code, and we use the median 2014 parish code for the other dwellings in this new parish code as the 2014 parish code for the new dwelling. In most cases this will be entirely correct, while, in a few cases, there will be a small measurement error.

Neighborhoods (parishes) are characterized by access to jobs, ER unit, school, and commercial activity. These are described in turn.

Given the address of all private and public companies we are able to compute the time travel distance between all combinations of parishes. Given the 2,179 different parishes (neighborhoods), this amounts to a total of approximately 2.4 million combinations. The distance measures were then linked to the registries' worksite information on number and type of employees. This enables us to compute the number of workplaces within a one-hour commute between all parishes.[29]

Commuting zones has a key advantage over other geographic units typically used for analysis of local labor markets: they are based primarily on economic geography rather than incidental factors such as minimum population or state boundaries.

We track the parish of all emergency room units (ER units) over time [30], and apply the computed parish-to-parish travel time distances to compute the time distance to the nearest ER unit across parishes and time.

Across years, we observe whether or not there is a school in a parish and whether or not the school offers all nine compulsory school grades (1^{st} to 9^{th}) or, alternatively, was a

[29]A common approach to measure job access is to use commuting zones, e.g., Autor and Dorn (2009) who use the commuting zones developed by Tolbert and Sizer (1996). Commuting zones have the advantage over other geographic units used for analysis of local labor markets that they are defined across state or other administrative boundaries. However, the our extremely detailed time-to-commute computations appear even more exact and are not subject to any choice of border between commuting zones.

[30]This information does not appear in the registries but was found in annual publications from the Danish Health Authorities 1992-2022, e.g., Sundhedsstyrelsen (1989). The parish was found using www.sogn.dk. We choose to focus on ERunits that are open round the clock.

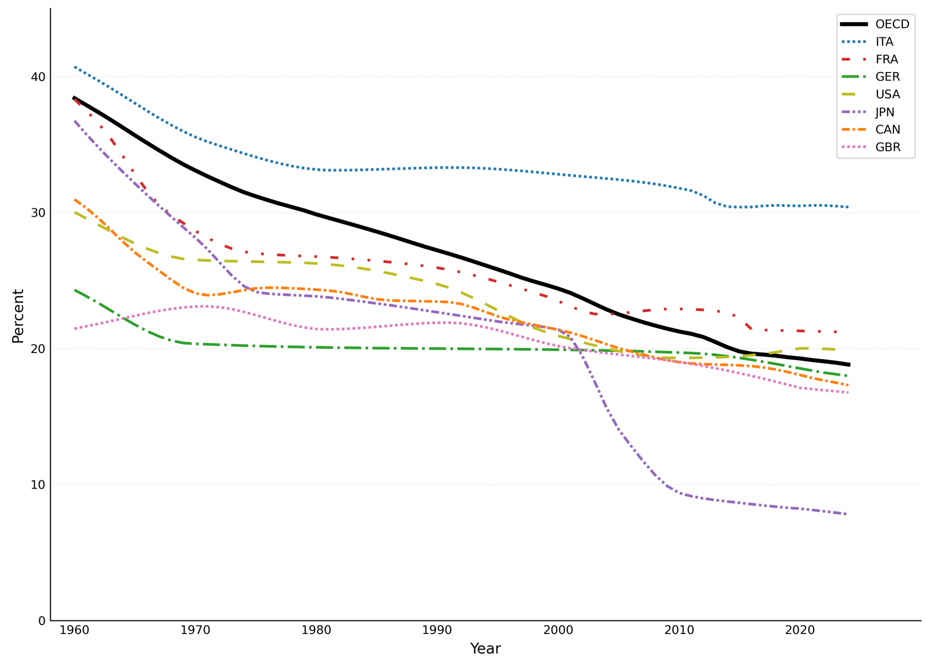
feeder school offering less than nine years.[31]

Commercial activity (grocery store) is observed through the VAT payments made by companies. For this paper, the interest is mainly in whether there is a supermarket, mini-market or the like as an indicator of the availability of the most basic daily life needs. The codes come from sector codes following NACE. There have been changes over the years.

D Appendix: Supplementary Tables and Figures

[31] In Denmark, most feeder schools offer up to 5^{th}, 6^{th} or 7^{th} grade, but it can also be up to 3^{rd} or 8^{th} grade. In our model, we treat all feeder schools alike. The information on feeder schools is available in the registries from the school year since 2007/2008 only. For earlier years the information was found in annual publications of the Danish handbook of schools (In Danish: Den Danske Skolehåndbog) combined with information from the Government Agency for IT & Learning (www.stil.dk). Feeder schools are usually found in rural areas.

Figure 8: G7 Percentages of populations living in rural areas, 1960-2024



Source: The World Bank Databank on Health and Nutrition and Population Statistics.
Note: Rural population refers to people living in rural areas as defined by national statistical offices. It is calculated as the difference between total population and urban population.

Table D1: Neighborhoods, 1992

	Neighborhood type				
	City	Town	Rural-city	Rural-town	Total
ER travel time	26.0	38.8	31.0	42.8	35.6
	(27.8)	(46.0)	(18.8)	(43.3)	(35.4)
Schools					
1-9 grade	86.0%	82.0%	24.0%	22.6%	39.9%
feeder	4.5%	11.5%	34.8%	29.6%	24.9%
None	9.5%	6.5%	41.2%	47.7%	35.3%
Job Access					
White Collar (Educ level)	2.6	1.1	1.7	0.9	1.5
	(1.3)	(0.8)	(0.9)	(0.8)	(1.1)
Blue Collar (Educ level)	1.6	0.7	1.1	0.6	1.0
	(0.7)	(0.5)	(0.5)	(0.5)	(0.6)
Commercial					
All	89.2%	90.6%	50.6%	50.2%	61.0%
Supermarket+discount	65.1%	59.7%	9.8%	10.6%	24.8%
#Parishes	445	139	646	928	2,158
Avg. population size	3,395	3,249	870	723	1,481
Total population	1,510,840	451,621	562,270	670,758	3,195,489

Table D2: Neighborhoods, 2022

	Neighborhood type				
	City	Town	Rural-city	Rural-town	Total
ER travel time	34.5	54.6	36.0	56.0	45.5
	(29.9)	(48.5)	(20.7)	(49.2)	(40.1)
Schools					
1-9 grade	82.6%	78.4%	28.0%	22.8%	40.2%
feeder	2.3%	6.5%	13.4%	9.1%	8.8%
None	15.1%	15.1%	58.6%	68.1%	51.0%
Job Access					
White Collar (Educ level)	4.9	2.0	3.4	1.7	2.9
	(2.3)	(1.6)	(1.7)	(1.5)	(2.2)
Blue Collar (Educ level)	1.8	0.8	1.3	0.7	1.1
	(0.8)	(0.6)	(0.6)	(0.6)	(0.8)
Commercial					
All	91.4%	89.2%	37.9%	36.6%	51.7%
Supermarket+discount	89.4%	87.1%	19.8%	19.0%	38.1%
#Parishes	445	139	647	928	2,159
Avg. population size	4,074	3,422	927	680	1,630
Total population	1,813,027	475,640	599,664	631,070	3,519,401

Table D3: Households, 1992

	Neighborhood type				
	City	Town	Rural-city	Rural-town	Total
Old Household	6.3%	8.2%	11.2%	13.2%	8.6%
Childfamilies	27.6%	33.4%	32.0%	30.4%	29.6%
Education					
Non-academic	32.1%	34.0%	43.8%	48.9%	37.2%
Academic	67.9%	66.0%	56.2%	51.1%	62.8%
Wealth (USD)	25,741	19,765	19,762	17,253	22,486
	(317,106)	(264,163)	(148,952)	(222,154)	(274,179)
Houseprice (USD)	167,457	144,282	187,117	168,445	167,610
	(103,017)	(107,898)	(184,172)	(185,841)	(137,240)
N	26,759	6,552	7,649	9,257	50,217
	(53.3%)	(13.0%)	(15.2%)	(18.4%)	(100.0%)

Table D4: Households, 2021

	Neighborhood type				
	City	Town	Rural-city	Rural-town	Total
Old Household	14.9%	18.9%	17.7%	20.5%	17.0%
Childfamilies	34.6%	34.1%	33.0%	29.7%	33.3%
Education					
Non-academic	16.6%	19.4%	24.1%	28.4%	20.5%
Academic	83.4%	80.6%	75.9%	71.6%	79.5%
Wealth (USD)	105,988	56,503	63,839	74,439	86,866
	(2,317,669)	(253,765)	(322,258)	(930,991)	(1,726,105)
Houseprice (USD)	405,346	258,377	379,805	307,886	364,135
	(297,121)	(255,085)	(531,807)	(510,058)	(392,197)
N	22,634	5,336	7,149	8,542	43,661
	(51.8%)	(12.2%)	(16.4%)	(19.6%)	(100.0%)

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