

Unveiling spatial mismatch in childcare supply and demand: An excess commuting analysis of home-to-childcare distance in subsidized families

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ABSTRACT

The distance between homes and childcare providers serves as a crucial factor in evaluating accessibility and equity in early childhood education. Spatial mismatch between childcare demand and supply is suggested when families opt for facilities further than the nearest available options, a situation scarcely scrutinized in existing literature, especially among under-six children from economically disadvantaged backgrounds. To fill this research gap, this study leverages the excess commuting analysis to delve into the extent of extended travel undertaken by subsidized families to access childcare services. Utilizing real enrollment data from the Florida's School Readiness program, it quantifies the disparity between actual and shortest possible commuting distances, investigating the tendencies of low-income families to forgo nearby providers for their young children. Furthermore, the research probes into age-related disparities in excess commuting, examining to what degree childcare facilities are more conveniently located for certain age groups compared to others. The analysis unveils substantial spatial mismatch in subsidized childcare, with a significant portion of low-income families choosing more distant providers, resulting in a 51.3% surplus in commuting distance. It also highlights a noticeable age-dependent trend in this mismatch: parents of infants face a dual disadvantage with longer commutes, compared to families with five-year-olds who have closer access to providers. The findings advocate for policy reforms that address these disparities, enhancing the efficiency and equity of childcare resource allocation.

1. Introduction

Access to childcare plays a crucial role in fostering positive cognitive and social development in young children (Peisner-Feinberg et al., 2001; Camilli et al., 2010; Sylva et al., 2011; Gialamas et al., 2014). However, it remains a significant challenge, especially for low-income families (Chaudry et al., 2011; Lipscomb, 2013; Krafft et al., 2017). Despite state and local subsidies to alleviate childcare expenses, these families continue to face hurdles in accessing childcare, including lower income levels, limited transportation options, higher transportation costs, and restrictive time-space budgets (Preston and Rajé, 2007; Andersson et al., 2012; Singh and Vasudevan, 2018; Fast, 2020). Notably, in Illinois and New York, many subsidy-eligible families struggle to access childcare due to residing in childcare deserts or being unable to utilize nearby providers due to capacity or program licensing constraints. Consequently, they often find themselves having to travel longer distances to access suitable childcare options, suggesting *spatial mismatch* between

childcare supply and demand (Sandstrom et al., 2018).

Within this context, understanding and quantifying the spatial mismatch, especially for subsidized families, is crucial (Denice, 2022). One commonly explored perspective involves examining residential proximity to schools or childcare providers, as demonstrated by various studies (Andersson et al., 2012; Boussauw et al., 2012, 2014; Dussailant, 2016; Cheng et al., 2017; Mei et al., 2019; Fjellborg and Forsberg, 2022; Mantovani et al., 2022; Blumenberg et al., 2024). The importance of shorter home-to-provider distances emerges as a critical factor in parental decision-making in early care and education (ECE), as highlighted by Shapiro et al. (2019). They emphasized that proximity to prekindergarten providers was the most critical factor in parental decision-making. Similarly, Dussailant (2016) observed a 3% decrease in enrollment likelihood for every 1-km increase in distance from the nearest childcare provider.

Typically, families are expected to prioritize providers in closer proximity to their homes to streamline their daily routines (Kawabata,

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2014; Langford et al., 2019; Fjellborg and Forsberg, 2022). This inclination towards nearer facilities seems even more pronounced among low-income families, largely due to their restricted time-space budgets and non-standard working hours (Sandstrom et al., 2018). The theory of transport-related social exclusion further sheds light on their limited mobility levels, underscoring the need for closer providers, due to inadequate access to transportation (Preston and Rajé, 2007). The U.S. Department of Transportation notes that around 20% of low-income families lack independent transportation, exacerbating the challenges of longer provider commutes. Consequently, a substantial portion of these families prioritize residential proximity in selecting childcare providers (Andersson et al., 2012; Herbst and Tekin, 2012; Li and Zhao, 2015; Singh and Vasudevan, 2018; Fast, 2020).

The balancing act between the desire for shorter home-to-provider distances and the limited access to suitable childcare compels these subsidized families to enroll their children in facilities that may not be the closest to their homes. The extra travel beyond the closest providers signifies spatial mismatch between childcare supply and demand, with the extent of the mismatch increasing as the extra commuting distance grows. Opting for the nearest provider without excess travel would indicate a well-balanced childcare supply and demand. Conversely, not enrolling in the closest provider results in an extended commute, underscoring spatial mismatch. In essence, the difference between the minimum and observed home-to-provider distances within a childcare market reflects the extent of spatial mismatch (Horner and Mefford, 2007; Cheng et al., 2017).

The tendency to travel additional distances for childcare access mirrors the concept observed in urban commuting studies known as ‘*excess commuting*,’ wherein individual workers may not opt for the closest job opportunities to their homes but instead pursue opportunities located at a greater distance (Hu and Wang, 2015; Hu and Li, 2021). Excess commuting quantifies the additional portion of a city’s actual commuting distance beyond what is considered the minimum, determined by the present configuration of residential and employment areas in the city (Hu and Wang, 2016; Jing and Hu, 2024). This concept was initially introduced by Hamilton (1982) to evaluate the effectiveness of the monocentric city model in predicting urban commuting patterns. Hamilton formulated a mathematical model to ascertain the minimum commuting distance, incorporating simulated population and employment data. Later, White (1988) devised a linear programming optimization technique that utilized actual land-use geography to calculate the minimum commuting distance—a method that has predominantly been adopted in subsequent studies. This technique identifies the optimal commuting connections between residences and workplaces by optimally matching workers to job opportunities, taking into account the demand size and supply capacity (Horner, 2008; Niedzielski et al., 2013; Hu and Li, 2021). In the context of journeys to childcare providers, the minimum commute represents the smallest degree of spatial separation between homes and providers that the current distribution of families and providers can facilitate. Given that the actual commute portrays the real spatial separation, the disparity between the actual and minimum commute consequently uncovers the extent of spatial imbalance between childcare supply and demand. This is pivotal in developing a more nuanced and accurate understanding of childcare access.

The excess commuting framework stands as a promising tool for delving into the patterns of journeys to care providers and enhancing our grasp on childcare access. Although the groundwork for its potential applicability in the general school commuting was laid by Horner and O’Kelly (2007), its integration into empirical studies, particularly within ECE settings, remains lacking, resulting in a substantial gap in contemporary literature.

In recent years, a select number of studies have attempted to examine the excessive nature of school travel patterns, though their methodologies rest on assumptions that may lack sufficient grounding. For instance, Boussaew et al. (2012, 2014) embarked on an exploration of discrepancies in actual and optimal travel distances to various

educational institutions, including kindergarten, primary school, middle school, and adult education, in Belgium. These studies scrutinized the excess rate of school travel, utilizing a ratio that quantified the gap between observed and potential minimum distances between homes and schools. A similar work was a study conducted in Changchun, China, which analyzed the variances in observed travel distances to kindergartens compared to the minimum potential distances (Cheng et al., 2017). Mantovani et al. (2022) brought a comparative lens to the discussion by evaluating the disparities in home-school distances between native and immigrant students during their critical final year of lower secondary education in two cities in Northern Italy.

However, a common drawback in these endeavors has been the simplistic method of calculating minimum travel distances, which generally entails assigning students to the nearest schools without factoring in the capacity of these institutions and the age of the children. This is where the excess commuting framework distinguishes itself as a more potent analytical tool. Equipped with a linear programming model, it accounts for both demand size and supply capacity, making it well-suited for such analyses.

This research aims to present a robust methodology to quantify the extended distances low-income families travel to access childcare services, thereby illuminating the spatial mismatch between childcare supply and demand. Specifically, it conducts an analysis of excess commuting patterns to childcare providers for families enrolled in Florida’s School Readiness Program that offers financial assistance to qualified low-income families seeking ECE. Recognizing the variations in the service capacity and the nature of care or education delivered across different age groups (Kawabata, 2014), this research also seeks to delineate potential age disparities in spatial mismatch among infants, toddlers, and preschoolers.

The contributions of this research are multifold. Firstly, it sheds light on the much-underexplored realm of commutes to childcare providers, a topic not as extensively scrutinized as commutes to primary or secondary schools. Secondly, it centers the analysis on subsidized families, a demographic significantly underrepresented in current literature. Moreover, this focus coupled with a detailed analysis across different age groups helps unveil nuanced behavioral divergences among the populations studied. Thirdly, as far as our investigations suggest, this study marks a first effort in applying the excess commuting analytical framework, traditionally utilized in geographic commuting literature, to the analysis of home-to-childcare commutes. Lastly, the state-wide scale of the analysis mitigates the potential impacts associated with edge effects (Ikram et al., 2015), which often result from relying on arbitrarily delineated geopolitical boundaries, such as counties, thereby promising more accurate insights.

2. Methodology

2.1. Study area and data source

The study area is the state of Florida. The population included in this study includes children under age 6 who were enrolled in the Florida School Readiness (SR) Program in June 2021. This program is intended to provide financial assistance for childcare to working, low-income families to support both their child’s development and their family’s progression to economic self-sufficiency. There are three populations who are eligible for the program: (1) children identified as “at-risk” by the child welfare system; (2) children participating in the Temporary Cash Assistance program or the Transitional Child Care Program; (3) families with a gross income of equal to or <150% of the Federal Poverty Line and are working or in school. The third accounts for a large majority of the SR population. About 11% of children under age 6 in Florida are currently in the SR Program, utilizing approximately 16% of all childcare slots in the state.

The data are provided by the Florida Division of Early Learning, who administers the SR program, and include child age, home street

addresses, and the address of the childcare provider in which they were enrolled. After removing records with missing or invalid home or provider street addresses the study population includes 95,520 children under age 6 served by 5159 providers. The Google Maps Geocoding API is used to geocode the addresses. Geographic Information Systems (GIS) data for the 2021 census tract boundary and road network are downloaded from the U.S. Census Bureau. To protect children's privacy, the journey to childcare for each of the 95,520 children is aggregated to the census tract level by a spatial join analysis in GIS. The childcare demand in each tract is calculated as the total number of children enrolled in the SR program who lived within the tract, and the provider supply in a tract is quantified by the total number of enrolled children.

Fig. 1 illustrates the spatial distribution of the supply-to-demand ratio by census tracts. Clearly, the supply is unevenly distributed compared to the demand, and most of the high-ratio tracts (dark blue) are clustered in major metropolitan areas such as the Miami, Orlando, and Tampa metros. This uneven distribution of supply relative to demand suggests a spatial imbalance in childcare.

2.2. Calculation of travel distance

This research measures the home-to-provider distance by the travel distance through the road network, which includes two components—interzonal and intrazonal travel distance. The interzonal distance is the road network distance from a home tract centroid to a provider tract centroid, while the intrazonal distance is measured by the radius of a circle approximating the area of the tract (Jing and Hu, 2022). The final travel distance between two tracts is derived by combining both interzonal and intrazonal distances, thereby accounting for the additional travel between home or provider locations and their corresponding tract centroids (Hu and Wang, 2016; Hu et al., 2020). Families traveling extremely long distance to the provider (> 80 km)

may represent reporting errors. To reduce the bias due to these extreme commutes, 151 children who traveled beyond 80 km (about 0.2% of the total children) are excluded from the subsequent analysis. There remain 95,369 children after the deletion.

2.3. Measurement of excess commuting

The mainstream linear programming method is used to model and analyze the excess provider commuting of children under age 6 in the SR program in Florida. By controlling for demand size and supply capacity, this method repeatedly rearranges the home-to-provider flow between census tracts until the total travel distance reaches the lowest possible level. In this optimal commuting scenario, children would attend the closest provider *overall*. This does not necessarily mean that each child would exactly go to their nearest provider, as it would then require that providers have unlimited capacity. Hence, the linear programming method is well-suited for this analysis. This method can be formulated as follows:

$$T_{min} = \min \left(\frac{1}{N} \sum_i \sum_j x_{ij} d_{ij} \right) \quad (1)$$

$$\text{Subject to : } \sum_j x_{ij} = C_i, \sum_i x_{ij} \leq P_j, x_{ij} \geq 0 \quad (2)$$

where the minimum home-to-provider travel distance T_{min} is derived by reallocating tract-to-tract commuting flows to reduce the total travel distance while maintaining the total number of children C_i and provider capacity P_j in each tract. Specifically, x_{ij} denotes the optimal number (nonnegative) of children living in tract i while attending providers in tract j , which is to be solved, d_{ij} is the travel distance between tracts i and j , and N is the total number of children in the study area. The objective

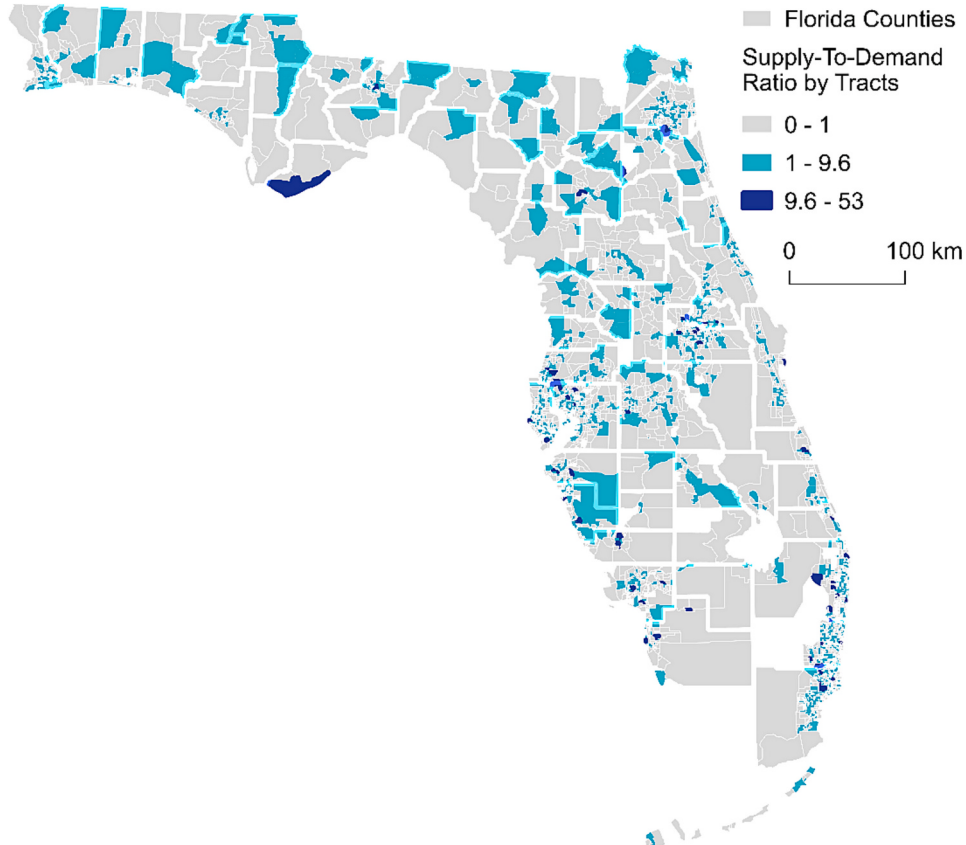


Fig. 1. Spatial distribution of the childcare supply-to-demand ratio in Florida.

function in Eq. (1) minimizes the average home-to-provider distance, and the model constraints in Eq. (2) ensure that each child is assigned to a provider slot, and the number of enrolled children is not greater than provider capacity.

Following the aforementioned distance estimation procedure the average observed home-to-provider distance T_{obs} can be obtained based on the actual enrollment flow pattern between tracts.

Excess commuting T_{ex} is then defined as the proportion of T_{obs} that exceeds T_{min} and is formulated in Eq. (3). It describes the derivation of the observed commuting distance from the minimum value given the existing spatial arrangements of families and providers in a study area. Therefore, it reflects the study area's potential to reduce its home-to-provider travel by parents enrolling their child in similar providers closer to home. A greater value of T_{ex} indicates a higher commute surplus and hence greater spatial mismatch.

$$T_{ex} = \frac{T_{obs} - T_{min}}{T_{obs}} \quad (3)$$

To obtain more meaningful estimates of excess commuting, this research disaggregates children into six age groups: infant (<1 year old, coded as INF hereafter), toddler (1–2 years old, coded as TOD), age 2 (coded as 2YR), age 3 (coded as PR3), age 4 (coded as PR4), and age 5 (coded as PR5). The linear programming method in Eqs. (1)–(2) is then applied to calculate T_{min} for each age group separately. This is to ensure that in the optimal scenario each child would only go to the nearest overall provider that offers services to the corresponding age group. The minimum travel distance for a general child T_{min}^{ALL} is then derived by calculating the weighted average distance by the number of children among age groups:

$$T_{min}^{ALL} = \frac{\sum_k C_k T_{min}^k}{\sum_k C_k} \quad (4)$$

where k refers to each of the six age groups, C_k is the total number of children in age group k , and T_{min}^k is the average minimum travel distance for age group k . Finally, excess commuting for an overall child T_{ex}^{ALL} or among age groups T_{ex}^k can be acquired by comparing T_{min} with T_{obs} specific to the group defined.

3. Results

3.1. Excess commuting for the overall children

For the overall children under age 6 in the Florida SR Program, families traveled 9.24 km on average to the provider of their choice. Only 13% of children attended providers within the same census tract where they lived, and about 87% of children left their home census tracts and chose providers elsewhere.

Results on T_{min} revealed that the existing spatial distribution of providers and subsidized families in Florida would support an optimized commute for the home-provider distance of 4.5 km. This distance reduction is a result of more children attending providers locally in a geographically optimized system. Compared to the 13% of within-tract commuting in reality, the optimal commute is associated with a much higher 41% of local provider commuters, suggesting a more balanced relationship between childcare demand and supply that the current spatial structure can sustain. The increase in within-tract commutes is evident from looking at the spatial flow patterns of the observed and minimum commuting systems in Fig. 2. It is clear that the commuting flow spatial structure becomes much more simplified in the geographically optimized system in Fig. 2B, which is largely attributable to the reduction in cross-tract commutes. In essence, T_{min} captures the overall spatial proximity between children and providers, and therefore it reflects the spatial accessibility to childcare that a given spatial arrangement of childcare demand and supply can foster. Clearly, this 4.5-km spatial proximity is too long for active travel mode and thus would most likely require car travel. As such, though much shorter than T_{obs} , this figure still demonstrates a relatively low level of childcare access for families using childcare subsidy in Florida.

A comparison between T_{obs} and T_{min} yields a 51.30% T_{ex} . Put it another way, over one half of the observed commute to childcare providers was longer than strictly necessary. The fact that the actual journey to childcare among these families was more than twice as long as needed signifies two possibilities. First, families may have traveled larger distances because there were no available slots at providers close to their residence. Or second, families could be compelled to select more distant providers due to non-geographic factors such as provider hours, price, or

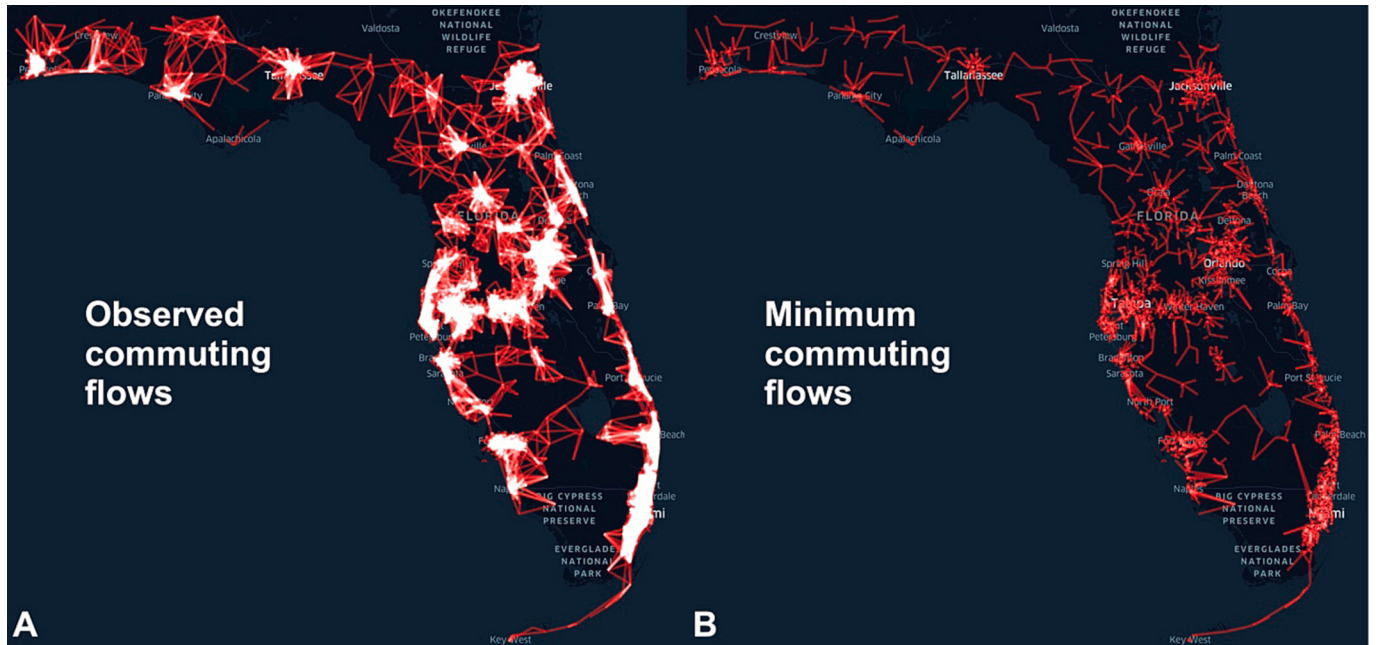


Fig. 2. Spatial patterns of observed commuting flows (A) and minimum commuting flows (B) for the overall children. For better visualization, within-tract flows are not visualized.

quality. In either case, it demonstrates great spatial mismatch between demand and supply.

3.2. Excess commuting among age groups

To examine whether, and to what extent, providers are more readily accessible, that is, closer to home, to one age group than another, a disaggregated analysis of excess commuting is conducted among six age groups. Table 1 highlights discernible age-related variations in both observed and minimum home-to-provider distances, which are supported by the one-way analysis of variance (ANOVA) at a 0.05 confidence level (F value of 15.92 and 30.67 for observed and minimum commuting scenarios, respectively). Subsequently, a post hoc Tukey-Kramer test is conducted for pairwise comparisons to determine groups with significantly different mean commuting distances. Fig. 3 presents the test results. Only statistically significant findings are discussed below. Regarding T_{obs} , the two youngest age groups (INF and TOD) traveled significantly longer distances to providers compared to the overall children, while the oldest age group (PR5) had significantly shorter distances. This is perhaps due to the limited provider capacity for children aged from birth to two years. As such, parents are more likely to travel greater distances in search of available spaces. Notably, among all age groups, INF had the lengthiest travel distance at 9.78 km, while PR5 had the shortest at 8.77 km, with a statistically significant difference between them. This significant difference is further revealed in Fig. 4 that plots the distance decay curve among age groups. For better visualization, the distance is cut off at 30 km. All these curves include two different trends. The left portion of the curve indicates an increase in the number of journeys to childcare with an increase in commuting distance, whereas the right part reflects the pattern that the number of journeys to childcare declines as the distance to providers increases. The tipping point in the curve shows the distance threshold where an age group changes their attitude towards distance. Clearly, PR5 and INF, respectively, had the smallest and largest distance tipping point. The smallest value for PR5 indicates that they were the most sensitive to distance when choosing a provider and hence had the shortest overall travel distance. Conversely, the largest tipping point for INF demonstrates that they had the greatest tolerance of long-distance travel and therefore commuted the farthest. Interestingly, a declining trend in distance tipping point appears as the child gets older, suggesting that families with younger children are more willing to bear longer travel to childcare.

In a geographically optimized system among age groups, the home-provider distance (T_{min}) largely decreased compared to T_{obs} . Interestingly, both T_{obs} and T_{min} displayed consistent distance rankings among age groups. For instance, compared to the overall children, both INF and TOD demonstrated significantly higher T_{min} , suggesting relatively limited childcare access for these two age groups than the general children.

In terms of T_{ex} , INF and PR5 had lower commuting surplus than the general children did (51.30%). Specifically, INF had the lowest excess commuting rate (46.83%), or the most economic commute, among age groups, followed by PR5 (50.29%). Interestingly, INF and PR5 were the

two extremes of either the actual or minimum commuting distance band—INF and PR5, respectively, having the largest and smallest values for both T_{obs} and T_{min} —and yet they both had a low degree of excess commuting. This is because that T_{ex} essentially captures the relative difference between T_{obs} and T_{min} , regardless of their actual values. The lowest T_{ex} , or high commuting efficiency, for INF is actually an outcome of higher actual travel distance and, at the same time, greater minimum distance. This dual disadvantage makes INF the most disadvantaged age group in terms of spatial imbalance and accordingly the journey to childcare. The greatest spatial imbalance for INF is most likely due to a limited supply capacity relative to demand (e.g., a longer waiting list) for this age group (Kawabata, 2014). This makes them search the furthest for availability. Instead, the high commuting efficiency for PR5 arises from both T_{obs} and T_{min} being low, implying the least spatial imbalance between childcare demand and supply for PR5. See Fig. 5 for the spatial flow patterns of observed and minimum commuting systems between INF and PR5. Flow visualizations for the rest of the age groups are not shown.

4. Concluding remarks

Home-to-provider distance is an important variable in measuring childcare access and equity. When the actual distance is longer than the minimum distance, it is an indication of spatial mismatch between demand and supply in ECE. Existing studies, however, have largely overlooked this critical geographic dimension among children under age 6, especially from low-income families. This research presents a first attempt to apply the excess commuting methodological framework to evaluate and quantify the spatial mismatch between childcare supply and demand. Specifically, it compares the disparity between observed and minimum provider commuting distances, aiming to understand the extent to which low-income families, with children under the age of 6 enrolled in subsidized childcare, do not enroll their children in the closest provider to their homes. It further examines age-related variations in the spatial mismatch among different age groups by testing whether, and to what extent, providers are more readily accessible, that is, closer to home, to one age group than another. Some key takeaway messages are presented below.

Firstly, a significant amount of excess commuting (51.3%) is observed, as the actual journey to childcare (9.24 km) is more than twice as long as strictly needed when they attend an alternative, nearby provider (4.5 km). As about 87% of children left their home tracts and chose providers elsewhere, it results in a much higher actual commute. The minimum home-provider distance analysis, however, suggests that the existing spatial configuration of childcare services could, in theory, support more local commutes (41%) and hence much shorter journey to childcare. As such, this indicates a great spatial imbalance between subsidized childcare demand and supply. Causes for the spatial imbalance can be multifaceted. It could be due to inefficient utilization of services, i.e., space at their local providers is mostly taken by families from other tracts. The excess commuting analysis in this paper can address this issue by suggesting the most efficient utilization pattern embedded in T_{min} . It may also be because that some families value provider characteristics more highly than the proximity of the provider to their home residence.

Secondly, the degree of spatial mismatch and the journey to childcare varies by child age. In both actual and minimum commuting scenarios, commuting distance tends to decrease as child age increases. As such, parents of infants had the longest (actual and minimum) home-to-provider distance, while parents of five-year-olds had the shortest. This trend is also evidenced from a distance decay analysis, which finds that parents of infants had the highest tolerance for longer travel while parents of children of five-year-olds had the lowest. Despite the contrasting commuting distance between parents of infants and parents of five-year-olds, they share similar, high commuting efficiency due to small deviations of the actual commuting distance to the minimum. The

Table 1
Excess provider commuting metrics.

Age group	T_{min} (km)	Percentage of within-tract commute	T_{obs} (km)	Percentage of within-tract commute	T_{ex}	Number of children
ALL	4.50	40.59%	9.24	12.96%	51.30%	95,369
INF	5.20	33.71%	9.78	12.86%	46.83%	5840
TOD	4.65	39.12%	9.64	11.87%	51.76%	14,303
2YR	4.42	42.50%	9.29	13.01%	52.42%	18,978
PR3	4.45	40.79%	9.20	12.83%	51.63%	21,529
PR4	4.40	41.50%	9.11	13.35%	51.70%	20,366
PR5	4.36	40.74%	8.77	13.66%	50.29%	14,353

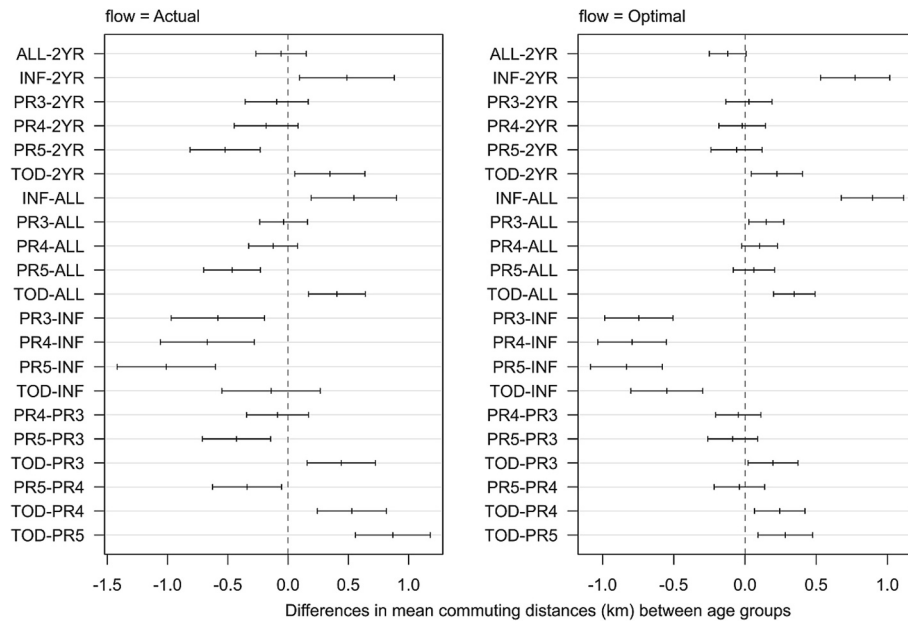


Fig. 3. Confidence intervals of one-way ANOVA with post hoc Tukey-Kramer test (confidence level = 0.05).

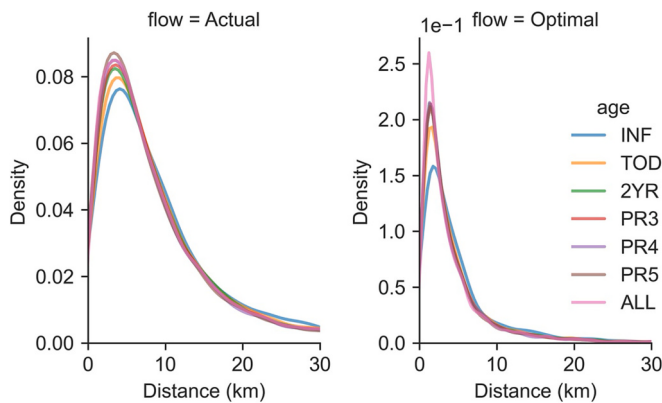


Fig. 4. Distance decay effect in the journey to childcare among age groups.

seemingly high commuting efficiency for parents of infants is actually an outcome of greater actual travel distance and, at the same time, greater minimum distance. This indicates the dual disadvantage in terms of spatial mismatch and the journey to childcare for this age group. Conversely, the high commuting efficiency for parents of five-year-olds is truly reflective of the least spatial imbalance and best childcare access for them, given the lowest values for both actual and minimum home-to-provider distance.

Thirdly, the proposed excess commuting methodology provides simple regional commuting statistics, such as the actual and minimum commuting distance, that can be easily understood and compared by policymakers and the general audience for evaluating spatial mismatch between childcare demand and supply. The excess commuting statistic is simply a relative percentage measuring to what extent a travel pattern can be reduced to an optimal level that the existing spatial configuration of housing and childcare services can foster. The flow visualizations in Fig. 2 and Fig. 5 provide effective visual tools for policymakers to better understand how families are using childcare services, identify and implement the optimal geographic utilization pattern of such services, and pinpoint areas suffering from the worst spatial mismatch. The methodology can be readily applied to other types of educational services and programs. As it involves analyzing the actual and optimal journey to childcare, it provides new insight into childcare access, from

both realized and potential perspectives.

Fourthly, this research offers several policy insights. The large excess commuting rate for the general families highlights inefficient use of childcare resources due to spatial mismatch between demand and supply. Utilizing the derived commuting statistics and flow visualizations, policymakers can assess the nonoptimal geographic utilization of educational resources and identify neighborhoods with the worst efficiency for targeted improvement. The flow pattern associated with the minimum commute could inform program creation to incentivize alignment with the optimal utilization pattern. In times of changing demand or supply, the analysis can be readily rerun to guide policy updates. The methodology also facilitates locational decision-making. By replicating the analysis among candidate provider locations, policymakers can pinpoint areas with the most significant potential for improving spatial imbalances. Additionally, it guides decisions on where to strategically support supply expansions and implement programs, such as subsidies, to enhance childcare access. It is important to note that our intent is to present this methodology as a guiding tool rather than enforce specific outcomes.

Policymakers should consider the identified age differences when formulating locational policies. The inverse relationship between age and travel distance, observed in both actual and minimum scenarios, implies that policymakers should avoid treating different age groups as having homogenous travel behavior. Given the uneven distribution of educational resources in reality, policymakers can devise specific locational policies tailored to each age group for more effective outcomes. For instance, prioritizing resources to enhance existing provider capacity or introducing new providers in supply-scarce neighborhoods could address the unique challenges faced by families with infants, who experience a dual disadvantage in their journey to childcare. Conversely, considering the minimal spatial imbalance for five-year-olds, policymakers may consider reallocating resources or adjusting spatial configurations between five-year-olds and infants to promote more equitable childcare access among age groups. Applying a uniform policy to all age groups could disproportionately disadvantage vulnerable groups, such as families with infants.

Findings from this research could also provide insights for childcare access research and policymaking. As pointed out by Davis et al. (2019), a standardized definition or metric of childcare access is lacking in the ECE domain. To bridge this gap, scholars have devised dichotomized

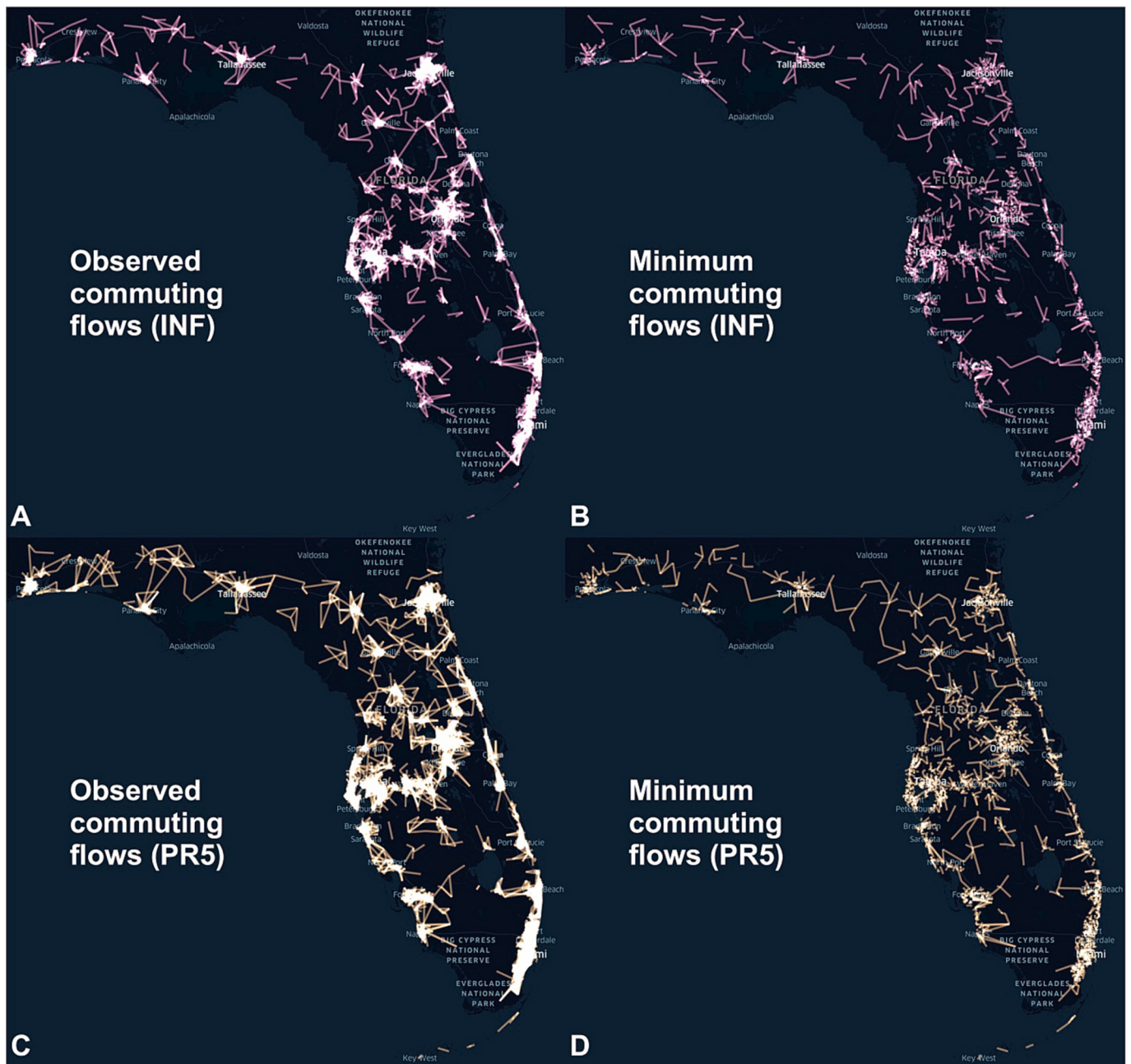


Fig. 5. Spatial patterns of observed commuting flows for INF (A) and PR5 (C) and minimum commuting flows for INF (B) and PR5 (D). For better visualization, within-tract flows are not visualized.

area-based aggregate (DABA) measures (Dobbins et al., 2016; Malik et al., 2018) and other distance-based methods (Davis et al., 2019) to measure childcare access. Upon reviewing these measures, a common assumption emerges, suggesting that all families ought to opt for childcare providers within a certain radius from their residences. However, determining such a cutoff distance poses challenges and, as evidenced by this research, is likely to vary among different groups of children, particularly those categorized by age. The identified actual and minimal home-to-provider distances among various age groups could serve as a reference in educational access policy studies that rely on distance cutoffs.

The policy implications of this research also extend to sustainable transportation. Studies have consistently highlighted that home-school distance is the most important factor in affecting mode choice (Jensen, 2008; Van Goeverden and De Boer, 2013). Longer distances to

school are often linked to motorized modes, contributing to peak-hour traffic and raising safety and environmental concerns (Scheiner, 2016). Implementing policies that encourage enrollment in the overall nearest childcare provider could alleviate traffic congestion and reduce air pollution. Furthermore, the optimal geographic utilization pattern could facilitate the adoption of more sustainable travel modes, such as dedicated bus transportation for providers, considering that most children reside in the same neighborhood as the childcare facility. This not only diminishes private vehicle traffic but also yields environmental benefits. Given that children's travel needs have a direct impact on household travel patterns, an analysis on the journey to childcare can guide policymakers in developing more efficient and equitable transportation and land-use investments, benefiting travelers of all ages and modes.

However, the above results and discussions may be tempered by

some limitations inherent to this study. Firstly, the primary objective of this paper is not an exhaustive exploration of factors influencing parental provider selection, but rather a focused examination and quantification of spatial mismatch between childcare supply and demand for subsidized families using an excess commuting perspective. While home-provider distance remains a crucial consideration, additional influential factors in parental decision-making encompass aspects such as quality, reputation, tuition costs, teacher qualifications, security, and operating hours of providers (Shlay, 2010; Sandstrom et al., 2018; Carlin et al., 2019; Davidson et al., 2020; Mantovani et al., 2022; Okitsu et al., 2023). Due to data constraints, this research does not incorporate these additional factors within the current analysis. Furthermore, some parents may prioritize selecting a childcare provider closer to their workplace rather than their residence (Dussaillant, 2016). While considering the excess commuting between the workplace and provider could be insightful, its omission from our analysis may have minimal impact given our specific focus on subsidized families. This demographic is likely to prioritize childcare facilities near their homes for convenience, aiming to reduce travel time and simplify drop-off and pick-up procedures, particularly considering their potential lack of reliable transportation. Additionally, research indicates that proximity to the family residence is a more crucial factor for low-income families when selecting childcare programs, while the location near the workplace holds greater significance for high-income families (Guyol et al., 2023). Relatedly, distance to grandparents or other family members who pick up children from the provider may also be relevant. Future research should consider these other distances when data are available. Secondly, this research does not account for competition from children not in the SR Program. Considering competition from all children can offer fuller insight into childcare access and spatial mismatch. Thirdly, findings from this study may be affected by the modifiable areal unit problem (MAUP; Horner and Murray, 2002; Hu and Wang, 2015), as the analysis is limited to a single level of aggregation. To gain a more comprehensive understanding of the MAUP impact, future studies could replicate the analysis at various levels of aggregation.

Author statement

The authors declare no competing interests.

CRediT authorship contribution statement

Yujie Hu: Conceptualization, Data curation, Formal analysis, Methodology, Visualization, Writing – original draft, Writing – review & editing. **Phillip Sherlock:** Conceptualization, Writing – original draft, Writing – review & editing. **Jing Huang:** Conceptualization, Data curation, Methodology, Writing – original draft, Writing – review & editing. **Herman T. Knopf:** Conceptualization, Resources, Writing – review & editing. **Jaclyn M. Hall:** Conceptualization, Writing – review & editing.

Data availability

The data that has been used is confidential.

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