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ORIGINAL RESEARCH

Navigating Demographic Uncertainty: Evaluating the Accuracy of Population Projections in Sweden's Major Municipalities

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Abstract

Population projections are essential tools for local government planning. This study examines the accuracy of population projections made by 26 municipalities in Sweden from 2010 to 2022. The findings reveal a mean absolute percentage error (MAPE) of 1.79% after 5 years and 3.29% after 10 years. The mean algebraic percentage error (MALPE), reflecting over- and underestimations, is 0.28% after 5 years and −2.17% after 10 years. Projections for 0-year-olds have a notably higher error due to difficulties in predicting births, while older age groups generally show improved accuracy except for the 19–24 age group. Births and deaths tend to be overestimated, whereas in- and out-migration are consistently underestimated. These results are generally consistent with previous studies in other countries. They also provide valuable insights for policymakers on expected error margins in population projections, thereby enhancing their utility for local governance. At the same time, the study adds to the literature by evaluating "real" municipal projections based on different local assumptions, examining both total populations and demographic components, and making use of high-quality register data. In addition, Sweden's dual system—where locally and centrally produced forecasts coexist—offers a rare opportunity to compare institutional approaches, providing insights of broader international relevance for both research and policy.

Keywords Population projections · Forecast accuracy · Mean absolute percentage error (MAPE) · Mean algebraic percentage error (MALPE) · Swedish municipalities · Demographic components

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Introduction

Population projections offer insights into expected shifts in resident numbers across various sub-groups. Consequently, they are indispensable for forecasting future demands in key sectors such as housing, infrastructure, education, and healthcare. They also play a vital role in understanding future resource trends, including changes in the tax base and purchasing power. Therefore, they form a critical foundation for planning activities at various levels of government.

Discussions on their accuracy (i.e., how close a projection turns out to be to the actual population development) began almost simultaneously with the earliest projection activities. This makes sense, as their inherent uncertainty poses a risk to planning decisions. Studies of population projection accuracy have often also examined whether, and to what extent, the size of a population (and that of various sub-groups) is over- or underestimated; in other words, the presence of projection bias. However, most evaluative work so far has concerned projections for countries or other large areas. Although activities such as residing, schooling and health care take place at a local level, and the context and prerequisites of the projections may vary geographically at this level of resolution, the evaluative literature of small-scale population projections is limited to just a few countries.

The objective of this article is to contribute Sweden's experience to the existing literature. This study aims to evaluate the accuracy of population projections made by 26 municipalities in Sweden from 2010 to 2022. Deviations between projections and actual outcomes are referred to as projection errors. The study period was marked by significant demographic turbulence, including a surge in immigration in the mid-2010s, the COVID-19 pandemic, and a notable decline in births in the early 2020s, potentially impacting projecting accuracy.

More specifically, this article addresses the following research questions:

- What is the mean absolute percentage error (MAPE) for municipal population projections in Sweden, i.e., accuracy? And to what extent do these projections tend to under- or overestimate actual population development; what is their mean algebraic percentage error (MALPE), i.e., bias?
- How does accuracy and bias change over the projection horizon, and are there any indications of systematic differences between municipalities?
- How do municipal population projections vary in these respects across various age groups and across the major demographic components?
- Are population projections based on local knowledge more accurate than those carried out centrally by Statistics Sweden?

Besides contributing to the scientific literature in this field, this study aims to enhance decision-makers' confidence in using municipal population projections and to provide valuable insights to those involved in the projection-making process. While municipal planners and decision-makers in Sweden (and likely other countries as well) are generally aware that projections are never exact, there has until now, been little systematic knowledge of the typical size of their errors. This lack of evidence has allowed both proponents and opponents of policy decisions to invoke popula-

tion uncertainty selectively—for example, by arguing that a population projection is "just a guess" and could be dramatically wrong in either direction. By clarifying the magnitude and direction of such errors, this study helps reduce uncertainty and lays the groundwork for a more informed use of projections in local planning and investment decisions.

Just as there is a multitude of small-area projection methods (for a recent overview, see Wilson et al., 2022), there are also various ways to evaluate them (for an overview, see Rees et al., 2019). Given the objectives and context of this study, we will use data from past periods and compare the projections with actual register data. This approach involves an "error analysis" type of evaluation, to use the terminology of Rees et al. (2019).

Background

Local Population Projections in Sweden

Municipalities in Sweden, as fundamental administrative units, are responsible for local governance and essential services, relying heavily on accurate demographic information for effective service planning. Firstly, the largest part of the municipal resource base comes from their right to tax their residents. Secondly, a smaller portion of their resources comes from Sweden's national system for financial redistribution between municipalities, but this system also places a strong emphasis on the demographic situation. Thus, the population structure of a municipality determines both the demands of its residents and its resource base to fulfill them.

The data used for population projections in Sweden do not rely on censuses but on yearly register data, which can be broken down by age, sex, and other individual attributes. The cohort-component method is almost exclusively employed. In Sweden, the first national projections using this method were carried out in the 1920s, followed by local equivalents in the 1940s (see Statens Offentliga Utredningar, 1945, chapter VIII, for a comprehensive compilation of Swedish population projections up to the mid-1940s). Each municipality is responsible for producing a population projection when needed. Although most municipalities do so on a regular basis, some create projections in-house, while others hire consultancies. In any case, the municipality has the final say regarding assumptions.

Nilsson (1981) describes the 1960s as a period when municipalities assumed new planning responsibilities, leading to formal municipal population projections replacing rough estimates based on rules of thumb. Since then, occasional national conferences have been held to encourage the exchange of knowledge and experiences.

Many Swedish municipalities conduct yearly follow-ups of their own projections (e.g., Bandel & Schéele, 1995; Schéele, 1981; Zeidlitz, 2007), but these exercises lack a broader context. To the best of our knowledge, proper studies of Swedish small-area projection accuracy are scarce and limited to single municipalities.

Moreover, since each municipality tends to make its own projection, there is no guarantee that these projections align to provide plausible national-level results. Gulbrandsen (1960) was the first to make regional projections for the entire country,

dividing it into (more than 100) sub-areas. Since then, aggregated projections for all of Sweden, broken down by municipalities and regions, have occasionally been produced (e.g., Amcoff & Westholm, 2007; Nygren & Persson, 2001).

Finally, starting in 2020, Statistics Sweden has regularly subdivided its national population forecast by regions and municipalities. An evaluation of these efforts has already been published, reporting decent accuracy at both the county and municipal levels over a three-year period (2020–2022). The errors were similar for both sexes but heightened for young children (Statistics Sweden, 2023). At the same time, the new forecasts have not always been welcomed by municipalities. Local governments have generally continued to produce their own (parallel) projections, where local knowledge can be incorporated into assumptions about the components. When municipal projections diverge from those of Statistics Sweden, municipalities have expressed concerns about being disfavored when state authorities and institutions base decisions on the latter. One practical advantage of the centrally produced forecasts, however, is that they are freely available to municipalities, which may lower barriers to their use, especially for smaller municipalities with limited analytical capacity. Against this backdrop, the availability of both sets of projections now makes it possible, for the first time, to directly compare the accuracy of centrally produced and locally produced forecasts. Such a comparison is important for evaluating whether incorporating local knowledge contributes to improved projection accuracy.

Uncertainty in Population Projections in Previous Research

Although there is a general literature on projection accuracy (for a recent overview, see Keilman, 2020), it has been found that the results of general accuracy studies cannot be readily applied to regional or local conditions. In a comparison of accuracy between various Norwegian projections Texmon and Keilman (1991) observe that a projection "which is accurate at the national level does not necessarily exhibit small errors at the regional level" (p. 113, see also Smith & Tayman, 2003). Unfortunately, studies on the accuracy of projections at detailed geographic levels remain relatively scarce. Based on an Australian study (Wilson & Shalley, 2019), the moderate interest from the academic community does not reflect a lesser need for knowledge among users of regional projections; rather, it indicates a substantial demand.

Nonetheless, a number of observations have been made, and conclusions drawn, in previous studies of projection errors in small areas. They will serve as a backdrop to our empirical examinations and indicate what results to expect. Observations related to spatial aspects will be presented first, followed by those attributed to the time dimension, and finally those related to cohorts.

As Müller (1987) noticed, an obvious difference between national and small-area projections is the internal migration (i.e. between small areas) considered in the second instance, but not the first. Thus, compared to national projections, an additional component must be projected in the small-area projections. Moreover, the smaller the small areas are, the more moves will cross borders and count as internal migration. To be able to localize projection errors, Müller also suggested a graphic representation to reveal any geographical patterns of deviations from the general accuracy. Such deviations have also been reported elsewhere, ranging from the expected finding that

projections in settings with extensive population changes had lower accuracy (e.g., Isserman, 1977; Murdoch et al., 1984) and higher bias (e.g., Smith & Shahidullah, 1995; Tayman et al., 2011) to less obvious patterns.

Given Müller's observation above, the reported connection between area size and accuracy (Ernst & Soyka, 2003; Wilson, 2012; Statistics New Zealand, 2016; Yamauchi et al., 2016; Danmarks Statistik, 2023) is also expected.

As the extent of migration partly depends on how areas are defined, accuracy is also expected to increase with population size. The high exposure to random fluctuations among small populations compared to large populations is expected to work in the same direction. This relationship between population size and accuracy is explicitly confirmed, for example, by Murdoch et al. (1984), Smith and Shahidullah (1995), Statistics Finland (2013), Smith and Rayer (2015), and some studies have tried to model it. Whereas Schéele (1981) used 150 subareas of Stockholm with 500–15,000 inhabitants, Tayman et al. (1998) used gridded Californian census data, randomly merged to reach 6000 areas of a few specified population sizes (500–50,000). Both of these studies estimated how projection accuracy can be predicted from population size. As a consequence, at a stipulated level of accuracy, reliable projection horizons for areas of various population sizes can be established. Wilson et al. (2018) introduce the concept of a "forecast shelf life" to communicate the implications of similar findings. However, population size does not seem to influence projection bias in any systematic way (Smith & Shahidullah, 1995; Tayman et al., 1998, 2011), although Rayer (2008) observes an indirect effect, as small populations tend to have larger population changes. Rayer et al. (2009) found that population change tends to be more consistently problematic for accuracy in the case of growth than in the case of shrinkage, whereas Cameron and Poot (2011) report the opposite.

It has long been clear that additional geographic attributes, beyond the basic demographic factors typically considered, may be important for population development (e.g., Murdock et al., 1991), whether an area is part of a larger labor market rather than being its own labor market (Simpson et al., 2020), labor market conditions more generally (Wilson & Rowe, 2011), or changes in real estate taxation regulations (Lux-Henseler, 2013).

Lenze (2000) reports a study in Florida, USA, showing that size, growth rate, and the elderly population—but not industrial specialization—affect projection accuracy. Tayman et al. (2011) found that information on prior error, geographical location, and the launch year could add explanatory power to small-area projection accuracy and bias, in addition to size and growth rate.

However, the most ambitious work of this kind has been carried out by Guangqing Chi and his colleagues. Chi (2009) introduces a large number of geographical characteristics but is still unable to produce a set of projections that is significantly more accurate than a simple extrapolation. He refines the method and considers information on adjacent areas in several follow-up studies but still cannot outperform the simpler alternative methods. The suggested explanation for this is temporal instability in the relationships between accuracy and its independent explanatory variables (Chi & Voss, 2011; Chi & Wang, 2017, 2018; Chi et al., 2011). Similar observations regarding the lack of improved accuracy from sophisticated projection methods have been made by, among others, Isserman (1977), Smith and Sincich (1992), and Rayer

(2008). This may also help explain why only limited progress in small-area projection accuracy has been observed over time (Rogne & Tønnessen, 2014; Wilson, 2012).

Even if more knowledge about accuracy cannot be used to improve projections, as these studies may suggest according to Chi and Wang (2017), it can still be useful for better interpreting the projections. This is the spirit in which the introduction and adaptation of stochastic methods to small-area projections (e.g., Grossman et al., 2024; Yu et al., 2023) can be understood.

Moving to the temporal aspects, the nearly self-evident relationship between accuracy and the length of the projection time was noted already by Schmitt and Crosetti (1953) and has been observed in nearly every study since. Smith and Sincich (1991) found that the deviation was linear over time. Rayer (2008) reports that bias also increases with the projection horizon, and Rayer et al. (2009) report that the bias tends to be positive in the early years of a projection but negative in its final years.

Simpson et al. (2020) emphasize the importance of recent base data (as there may be several years between censuses in many countries) for achieving the best possible accuracy. The launch year itself is also reported to be important for both accuracy and bias (Rayer, 2008; Tayman et al., 2011).

Moreover, studies have also focused on the potential importance of using a long base period (i.e., the past period of time from which factual population data is sourced to base assumptions). Rayer (2008) found that the length of the base period seems to have a limited impact on accuracy and bias, and Rayer and Smith (2010) identify a threshold, meaning that the accuracy of projections improves as the base period is extended, but only up to 10 years. Rogne and Tønnessen (2014) considered the temporal context when they reported that changes in migration (with subsequent impact on population projections) may be related to the pace of urbanization. Henry and Gutierrez (1977) shed light on the possible effects of time-specific circumstances more generally. Based on a study employing (basic) population data for regions and cities of France over 150 years, they suggest how the population development during base periods (of various lengths) relates to the subsequent development of these areas. Unfortunately, they found temporal differences and were unable to identify an ideal length for the base period.

Finally, attention turns to various subgroups within the population. Since young adults belong to the age groups most likely to move, their relocation is expected to be the most difficult to project. This is confirmed in most studies considering age. Small children (often not yet born at the time of the projection) are also found to display high error rates (e.g., Baker et al., 2021; Rees & Wilson, 2023; Reinhold & Thomsen, 2015; Statistics New Zealand, 2016; Wilson, 2012). However, Smith and Tayman (2003), Lux-Henseler (2013), Baker et al. (2021), and Rees and Wilson (2023) found lower accuracy for retirement-age groups. The first pair of authors suggests that this may be due to special circumstances in Florida, where their study was conducted, while the latter dismiss it as noise from small-sized age groups.

There may be reasons to divide a population into groups based on more criteria than age. For example, it is well established that highly educated women have lower-than-average fertility rates and that singles have a higher propensity to migrate. Rayer and Smith (2010) establish that separate sub-projections for specific populations enhance accuracy, as long as the assumptions for such sub-projections are suf-

ficient. Rees et al. (2019) draw similar conclusions based on the analytical separation of ethnic groups.

Data and Methods

Data Coverage and Projection Horizons

Sweden stands out compared to many other countries studied in the academic literature on population projections due to its excellent data availability. The residence of every inhabitant is registered at a specific dwelling and property unit, with known locational coordinates, along with information on age, sex, and other demographic details. Life course events such as births, moves, and deaths are continuously monitored, although population projections (as well as most other uses of these data) are typically based on yearly extracts from the registers compiled by Statistics Sweden. This practice of maintaining detailed population registers dates back to the eighteenth century. At the municipal level, assumptions can also be supported by local knowledge about planned housing developments, expansions, or downsizing of local activities, etc.

In 2023, we contacted the 30 most populous municipalities in Sweden, requesting population projections for the period from 2010 to 2022. Additionally, we sought more detailed information, including projections for specific age groups, demographic components, and associated reports. Ultimately, we successfully obtained population projections from 26 municipalities,[1] as outlined in Table 1. The average population size for these municipalities is 182,000 (with a median of 114,000). Stockholm is the most populous municipality, with 985,000 inhabitants, while Sollentuna has the smallest population at 76,000. Together, these 26 municipalities account for nearly 45% of Sweden's total population. The metropolitan areas included in the study (certainly Stockholm) consist of both central and suburban municipalities, whereas the medium sized cities tend to constitute labor market areas in their own right.

Most municipalities provided projections for the total population covering the years 2010 to 2022. However, data on demographic components (births, deaths, and in- and out-migration) and projections for one-year age groups were less comprehensive. There was also some variation in the projection horizons across municipalities. However, the majority reported a minimum projection horizon of at least 10 years, which served as an appropriate cut-off for our main analysis. In our study target year 1 denotes the first year covered by the projection.[2]

Unfortunately, few projections distinguished between internal and international migration, limiting our analysis to in- and outmigration as a whole. The 26 municipalities studied here are also a limited number compared to the 290 in the coun-

[1] Data are missing from four municipalities. Gävle (103,000 inh. in 2022), Luleå (74,000 inh. in 2022), and Växjö (97,000 inh. in 2022) are regional centers in different parts of Sweden. Solna (85,000 inh. in 2022) is closely integrated with the capital, Stockholm.

[2] If a projection is made for example in 2015, target year 1 refers to the projection for 2015, which is based on the reported population as of December 31, 2014, and forecasts the population as of December 31, 2015. Thus, the last observed year is 2021.

Table 1 Municipalities that provided population projections, type of data and target years

Municipality	Total population	Gross components	One-year age groups
Stockholm	2010–2022	–	2010–2022
Göteborg	2014–2022	–	2014–2022
Malmö	2010–2020, 2022	2013–2015, 2019–2020	2018
Uppsala	2010–2022	2010–2022	2013, 2016–2022
Linköping	2010–2022	2014–2022	–
Västerås	2010–2022	2010–2022	2012–2022
Örebro	2017–2022	2017–2022	2017–2022
Helsingborg	2010–2022	–	2010–2011, 2016–2022
Norrköping	2010–2022	–	2010–2022
Jönköping	2010–2022	2010–2022	2010–2022
Umeå	2010–2022	2021–2022	–
Lund	2010–2022	2019–2022	–
Huddinge	2010–2022	–	–
Borås	2010–2012, 2014, 2016–2020	2010–2012, 2017, 2019	–
Nacka	2013–2022	2018–2022	2013–2022
Eskilstuna	2010–2022	2010–2022	2010–2022
Halmstad	2011–2022	2020–2022	–
Södertälje	2010–2022	–	2010–2022
Sundsvall	2014–2022	2014–2022	2014–2022
Haninge	2015–2021	2015–2017	–
Karlstad	2010–2022	2010–2022	2010–2022
Botkyrka	2010–2022	–	–
Kristianstad	2012–2022	2012–2022	2012–2022
Kungsbacka	2019–2022	2020, 2022	2019–2022
Järfälla	2010, 2013–2022	2022	2010, 2013–2020, 2022
Sollentuna	2010–2022	2015–2022	2015–2022

try. Moreover, the time period is short and may be exposed to unique circumstances affecting projection accuracy.

Methods for Assessing Projection Accuracy and Bias

For our calculations, we primarily utilized the mean absolute percentage error (MAPE), a widely adopted metric in the relevant literature for assessing the accuracy of population projections (Rayer, 2007). It is calculated as:

$$MAPE = \sum |PE_t| / n,$$
$$PE_t = [(PP_t - A_t) / A_t] \times 100$$

where *PE* represents the percent error, *t* denotes the target year, *PP* signifies the population projection, *A* stands for the actual population according to Statistics Sweden, and *n* is the number of observations. Thus, as time goes by and the target year is reached, the MAPE measures the difference (in percent) between the actual and projected population.

To identify any issues of MAPE values being heavily influenced by single outliers, we also examined the Median APE (MedAPE), which represents the median of the absolute percentage error.

MAPE was employed to assess the accuracy of total population projections, demographic gross components, and age-group projections. While one-year age groups were obtained from several municipalities for the age-group analysis, aggregated age groups were acquired from additional municipalities. To maximize the number of observations and still capture age groups relevant to the municipalities providing data, the data were ultimately aggregated into eleven age groups (0, 1–5, 6–9, 10–12, 13–15, 16–18, 19–24, 25–44, 45–64, 65–79, 80+).

Given our interest in understanding the bias in the population projections (including potential outlier effects), we also computed the mean and median algebraic percentage error (MALPE/MedALPE) using the same formulas as for MAPE/MedAPE but including positive and negative values (to reveal over- or underestimations) instead of absolute values.

Finally, in addition to municipal projections, we also include Statistics Sweden's municipal-level projections, which have been produced annually since 2020. As these forecasts currently cover only a short time span (three target years), and since only a subset of our municipalities provide directly comparable data for this period, the comparison with municipal projections should be interpreted with caution. To ensure comparability, this part of the analysis is restricted to mean absolute percentage error (MAPE) for the total population and the four demographic components.

Results

Projection Accuracy: Time and Space

Figure 1 illustrates the average error over a 10-year projection horizon (see Online Supplement Table S1 for details). Overall, the results reveal a clear and gradual increase in error over time. Projections are very accurate in the first few years but become progressively less correct, reaching their peak error after 10 years. The median absolute percentage error (MedAPE) closely follows the MAPE values, suggesting that outliers are not a significant issue.

The MALPE, which sums the projections' biases (overestimations or underestimations), indicates that the projection errors largely offset each other, at least for the first six target years. However, from the seventh to the tenth target year, the proportion of projections underestimating the actual population exceeded the proportion of overestimations. Specifically, for target year 10, a notable 74% of all projections showed an underestimation of the actual population. The median algebraic percentage error (MedALPE) and MALPE show only negligible differences.

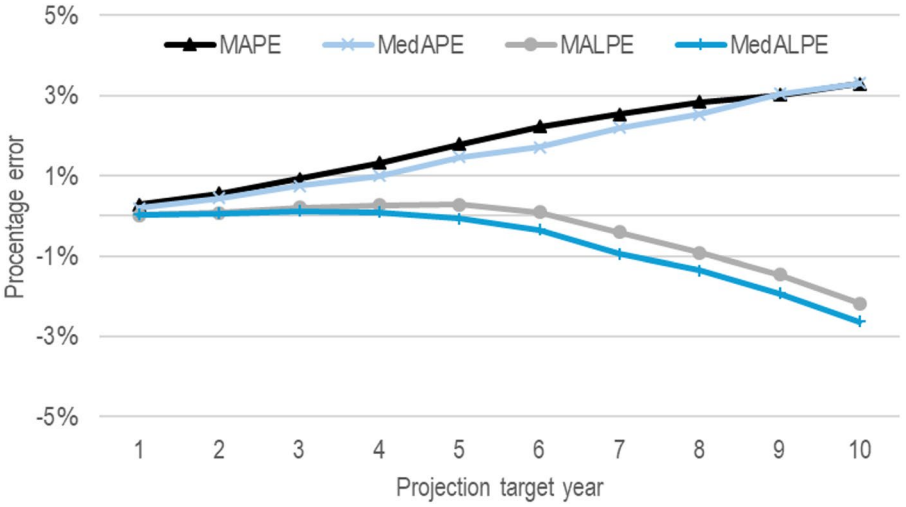

Fig. 1 Projection accuracy for the total population projections (MAPE, MedAPE, MALPE and MedALPE)

Fig. 2 Projected Population Growth and Turn-out in the Studied Municipalities 2010–2016 (left) and 2016–2022 (right). Bubble size equals population size. Big city municipalities are represented by blue bubbles and names in bold, suburban municipalities by bubbles in purple and names in Italic, and Regional centers by green bubbles and names in upright style

It should be noted that the projections obtained from the municipalities may contribute to the larger spread across the target years, as not all municipalities had the same 10-years coverage. For example, while target year 1 is based on 293 projections, target year 10 is based on 67 projections.

A closer examination of variations between municipalities (Fig. 2) indicates that we cannot confirm the conclusions from previous studies (e.g. Schéele, 1981; Tayman et al., 1998). We cannot detect any effect of population size on projection accuracy, nor any impact of other geographical characteristics (e.g., labor market status or

area size). A more detailed account is provided in the Online Supplement (Table S2). This conclusion is supported by a regression of log-transformed percentage errors on log population size, which yielded an almost flat slope ($\beta = -0.09$) and negligible explanatory power ($R^2 < 0.02$). However, Fig. 2 reflects differences between the first and second halves of the studied period. Whereas a general underestimation of the 2016 population can be observed in the projections launched in 2010, the opposite pattern occurs in the subsequent years.

Projection Accuracy: Age Groups

Municipalities often tailor their services to specific demographic groups, such as children or elderly. Therefore, the precision of population projections for distinct age groups is of significant practical importance, compared to overall population accuracy. Table 2 presents the MAPE for various age groups across specific target years.

It is noteworthy that the MAPE for 0-year-olds is considerably higher, ranging from about 3 to 13 times greater (depending on the projection target year) compared to the MAPE for the total population. This outcome is expected, considering that these children were not yet born at the time of the projection. However, recognizing that approximately 50 percent of one-year-olds in Sweden attend preschool (Viklund & Duvander, 2017), forecasting future population sizes for young age groups remains crucial for municipal planning. Although the MAPE decreases substantially for the next age group, 1–5-year-olds, it still remains 1–2 times higher than that for the total population.

For age groups ranging from 6 to 18 years, the MAPE closely aligns with the overall population MAPE, though slightly elevated. The 19–24-year-olds constitute an age group with the highest migration propensity across all moving distances (Niedomysl & Fransson, 2014). Therefore, it is unsurprising that this group has the second-highest MAPE, after the 0-year-olds. Similarly, the 25–44-year-olds exhibit a higher MAPE than the total population, but at a lower level compared to the 19–24-year-olds. Again, this is somewhat expected, as this older age group is relatively less prone to migration.

Predicting the three oldest age groups (ages above 44 years) seems relatively straightforward, as they, with only a few minor exceptions, consistently show lower MAPE values compared to the total projected population. However, it is worth noting that the 45–64 and 65–79 age groups have lower MAPE values than the 80+ age group. Nevertheless, it is important to consider that the oldest age group has a higher mortality rate and encompasses fewer individuals compared to the other two, which may contribute to the observed variations in projection accuracy.

Once again, we investigated the tendencies for biases within different age groups (Table 3). We observed a significantly higher proportion of overestimations for the 0-year-olds compared to other age groups. The MALPE values for the 0-year-olds closely mirrored the MAPE values, indicating consistent overestimations by municipalities for this age group. The 1–5 and 19–24 age groups were also consistently overestimated, though to a lesser extent than the 0-year-olds. For the remaining age groups, there was a relatively equal distribution between overestimations and under-

Table 2 Mean Absolute Percentage Error (MAPE) for the Total Projected Population and Projections for Age-Groups

	MAPE total population	Age-groups											Number of projections
		0	1–5	6–9	10–12	13–15	16–18	19–24	25–44	45–64	65–79	80-w	
Projection target year													
1	0.27	**3.81**	*0.62*	0.47	0.48	0.44	*0.88*	**1.39**	0.48	0.19	0.21	*0.58*	179
2	0.55	**5.75**	*1.31*	0.94	0.88	0.76	*1.44*	**2.69**	0.94	0.36	0.36	0.81	162
3	0.91	**8.01**	*2.39*	1.47	1.37	1.22	*1.99*	**3.99**	1.48	0.57	0.55	1.01	146
4	1.32	**10.18**	*3.66*	1.97	1.88	1.62	2.45	**5.31**	2.12	0.78	0.78	1.26	129
5	1.86	**12.09**	*5.29*	2.62	2.39	2.08	2.88	*6.66*	3.06	1.03	1.05	1.43	112
6	2.36	**13.58**	*6.73*	3.31	3.06	2.58	3.19	*7.61*	3.96	1.33	1.27	1.48	95
7	2.65	**13.28**	*6.68*	4.08	3.69	3.14	3.40	*7.86*	4.56	1.53	1.38	1.65	79
8	2.81	**12.11**	*6.46*	4.42	4.15	3.66	3.38	*7.84*	5.14	1.64	1.33	1.86	64
9	2.90	**11.10**	5.77	4.64	4.51	4.32	3.47	*7.80*	*5.86*	1.72	1.20	1.92	50
10	3.37	**10.28**	5.09	5.19	5.13	5.22	3.87	*7.64*	*6.81*	1.97	0.96	2.10	37

Italics cells indicate that the MAPE for these age-groups is at least two times higher than the MAPE for the total population, while bold cells signify a difference of at least four times

estimations, with a tendency toward higher overestimations as the projection horizon increased.

As shown in Table 1 not all municipalities provided age-group data for every target year, resulting in an uneven dataset. To address this, Tables 2 and 3 were recomputed (see Online Supplement Tables S3 and S4) with the 28 projections that covered all years. The overall patterns remain, 0-year-olds have the highest percentage errors, followed by those aged 19–24. However, errors in the early years are significantly smaller for these groups in the recomputed results. Regarding bias, several projections that had overestimated the population shifted to underestimation.

Projection Accuracy: Demographic Components

The precision of projections, whether for the entire population or specific age groups, depends on the dynamics of the four demographic components. Table 4 shows the MAPE and MALPE values over the ten-year projection horizon. Notably, both MAPE and MALPE values are significantly higher compared to those observed in total population projections. Interestingly, when examining the MALPE values, a distinct pattern emerges: the natural growth components (births and deaths) consistently show overestimation, while the migration components exhibit underestimation.

A closer examination shows that the MAPE values for the birth component display a clear upward trend during the first half of the projection period, followed by stabilization and a slight decrease toward the end. In contrast, the MAPE values for the death component remain relatively stable, with only minor variation. Deaths also constitute the component with the lowest average errors compared to the other three. Notably, MALPE values for births consistently demonstrate overestimation, maintaining levels similar to the MAPE values. In contrast, MALPE values for deaths do not exceed ± 1.5% in any target year.

Shifting the focus to in- and outmigration, both components show notable MAPE values. In-migration shows the highest average error of any component by the tenth year, with out-migration following a similar but slightly more moderate trajectory.

Remarkably, both in- and outmigration show negative MALPE values, consistently underestimating actual numbers. The similarity between MAPE and MALPE values suggests a systemic trend of underestimating migration in most projections.

Projection Accuracy: Municipalities Versus Statistics Sweden

Table 5 compares the MAPE of municipal projections with those produced by Statistics Sweden (SCB) for the total population and the four demographic components over a three-year horizon. SCB succeeds in predicting births better than the municipalities, but the situation is reversed for outmigration. Results for total population, deaths and in-migration are mixed. Additional tests (not shown), with more observations for total population MAPE, indicate that municipal projections are consistently more accurate than those of SCB (e.g., MAPE 0.32% vs. 0.40% in year 1, 0.69% vs. 0.81% in year 2, and 1.25% vs. 1.42% in year 3). Although the differences are generally modest and the comparison is limited by the short horizon and small number

Table 3 Mean algebraic percentage error (MALPE) for the total projected population and projections for age-groups

	MALPE total population	Age-groups											Number of projections
		0	1–5	6–9	10–12	13–15	16–18	19–24	25–44	45–64	65–79	80-w	
Projection target year													
1	0.02	**2.23**	0.01	0.03	0.01	*0.06*	**−0.06**	**0.66**	**−0.14**	−0.01	*0.04*	**−0.11**	179
2	0.11	**4.48**	*0.33*	0.07	−0.03	0.04	0.03	**1.57**	*−0.21*	0.01	0.10	*−0.21*	162
3	0.27	**6.74**	**1.16**	0.11	−0.11	0.01	0.17	**2.62**	−0.24	0.04	0.21	−0.26	146
4	0.37	**8.80**	**2.12**	0.06	−0.27	−0.26	0.14	**3.60**	−0.34	0.04	0.33	−0.36	129
5	0.45	**10.63**	**3.20**	−0.01	*−0.58*	*−0.60*	−0.02	**4.51**	*−0.57*	0.06	0.53	−0.33	112
6	0.34	**11.72**	**4.11**	*−0.37*	**−1.06**	**−1.16**	*−0.48*	**4.85**	*−0.98*	−0.04	*0.69*	−0.25	95
7	−0.28	**11.11**	**3.74**	*−0.79*	**−1.64**	**−1.73**	*−1.06*	**4.55**	**−2.15**	−0.28	*0.80*	−0.28	79
8	−0.99	**10.56**	*2.78*	−1.67	*−2.65*	*−2.95*	*−2.10*	**3.67**	*−3.53*	−0.76	0.64	−0.55	64
9	−1.89	**9.48**	1.60	−2.73	*−3.80*	*−4.09*	−2.72	2.74	*−4.92*	−1.32	0.39	−1.00	50
10	−2.86	*8.01*	0.19	−4.06	−5.00	−5.22	−3.36	1.25	*−6.18*	−1.90	−0.05	−1.57	37

Italics cells indicate that there is at least two times higher error between the MALPE for the different age-groups and the MALPE for the total population projection, while bold cells signify an error greater than four times

of observations, the findings suggest that incorporating local knowledge does not reduce accuracy and may, in certain respects, provide an advantage.

Discussion and Conclusion

This article aimed to assess the accuracy of population projections made by 26 major municipalities in Sweden from 2010 to 2022, a period marked by significant demographic shifts, notably in migration patterns. The results indicate a MAPE of 1.79% after 5 years and 3.29% after 10 years, with a MALPE of 0.28% after 5 years and -2.17% after 10 years. Projections for 0-year-olds exhibit notably higher MAPE values, reflecting the challenge of predicting births, while projections for older age groups generally show greater accuracy, except for 19–24-year-olds. Births and deaths tend to be consistently overestimated, while in-migration and out-migration are consistently underestimated. Births exhibit increasing errors over time, while deaths remain relatively stable with low errors. In contrast, errors in both in-migration and out-migration rise over the projection period, with out-migration showing slightly lower, yet still significant, errors. Notably, both migration components consistently demonstrate underestimation, highlighting a systemic trend in projection accuracy. Finally, in contrast to previous studies (e.g., Smith & Rayer, 2015; Tayman et al., 1998) we find no indications of systematic differences between municipalities of various types.

Compared to the accuracy reported in studies conducted in other countries (e.g., Rogne & Tønnessen, 2014; Wilson et al., 2018), the accuracies in this study stand out well. MAPE tends to be a few percentage points higher in previous studies. One obvious factor that helps explain this difference is the comparably large populations in the studied municipalities, as MAPE has been shown to decrease with population size. The availability of current and detailed register data is also an advantage which has not been well-explored in the previous literature. A third factor that may contribute to the comparatively good accuracy is that the projections evaluated were conducted by municipal officials with substantial local knowledge, whereas most projections in previous studies were centrally carried out for a whole set of small areas.

The results regarding bias in total population projections generally correspond with previous studies (e.g., Rayer, 2008; 2019), indicating a relatively stable bias in the first six target years (with a slight positive tendency), followed by a shift toward negativity from the seventh to the tenth target year. However, we are unaware of other studies that report contrasting MALPEs for the natural versus migratory components of the demographic equation.

The lack of differences between the studied municipalities, whether in terms of population size or other characteristics, may be explained by a few differences between this study and previous ones (e.g. Schéele, 1981; Tayman et al., 1998). Firstly, we have studied relatively few municipalities (26) spread out over a whole country, some in bourgeoning regions, others in waning surroundings. Secondly, the projection models and assumptions vary between them. Thirdly, although they can be seen as small areas, their populations are much larger than in most previous studies.

Table 4 Mean absolute percentage error (MAPE) and mean algebraic percentage error (MALPE) for demographic component projections

	MAPE total population	MALPE total population	Births		Deaths		In-migration		Out-migration		Number of projections
			MAPE	MALPE	MAPE	MALPE	MAPE	MALPE	MAPE	MALPE	
Projection target year											
1	0.26	0.02	**4.31**	**2.94**	**4.34**	**0.88**	**5.17**	**−3.42**	**5.25**	**−4.39**	138
2	0.52	0.07	**5.83**	**4.76**	**4.32**	**0.68**	**6.95**	**−4.43**	**6.90**	**−5.83**	122
3	0.80	0.07	**8.18**	**6.92**	**4.50**	**0.76**	**8.49**	**−5.61**	**7.36**	**−6.54**	108
4	1.11	−0.09	**9.94**	**8.44**	**4.86**	**0.68**	**9.95**	**−7.92**	**8.47**	**−8.04**	93
5	1.51	−0.32	**11.14**	**9.26**	*4.81*	*0.41*	**12.03**	**−10.07**	**10.03**	**−9.70**	79
6	1.88	−0.77	**12.63**	**10.43**	*4.68*	−1.03	**13.52**	**−12.68**	**10.49**	**−10.32**	64
7	2.32	−1.46	**12.45**	**9.69**	*4.76*	−0.97	**15.68**	**−15.12**	**11.62**	**−11.51**	52
8	2.82	−2.08	**12.53**	**9.75**	4.20	−0.91	**16.83**	**−16.55**	**13.00**	**−12.85**	42
9	3.02	−2.77	**12.13**	*9.15*	4.26	−1.09	**17.66**	**−17.62**	**13.70**	**−13.70**	31
10	3.78	−3.75	*9.91*	*6.67*	3.89	−0.08	**19.62**	**−19.62**	**16.18**	**−16.18**	22

Italics cells indicate that there is at least a two times higher error between the MAPE/MALPE for the demographic component projection and the MAPE/MALPE for the total population projection, while bold cells signify an error greater than four times

The differences over time, and the contrasting MALPEs for births versus migration, can be explained by shifts in demographic and migratory patterns. During the first decade of the twenty-first century the immigration to Sweden doubled, and after a considerable increase, the TFR approached almost 2.0 in 2010 (when the first projections studied were launched). However, in 2015 immigration policies became stricter and were explicitly intended to distribute the incoming population evenly between large and small municipalities. The immigration dropped even more during the COVID-19-pandemic. Additionally, the TFR declined slowly during the 2010s, then more rapidly from 2020. None of these developments could have been foreseen by the forecasters.

The comparison with Statistics Sweden's recently launched municipal-level projections provides a first indication of the potential value of local knowledge. Although the observation period is still short and the number of comparable cases limited, the results suggest that municipal projections perform at least as well as centrally produced ones, and in some cases more accurately. Supplementary tests based on a larger set of observations for total population reinforce this pattern, consistently showing lower MAPE values for municipal than for SCB projections. These findings point to an important institutional dimension: Sweden currently has two parallel forecasting systems, one based on centrally produced open-data projections and one relying on municipalities' own expertise and contextual knowledge. This dual arrangement is rare internationally and can be seen as a natural experiment, offering new opportunities to study how different institutional setups affect forecast accuracy.

Our results tentatively suggest that the incorporation of local knowledge may provide an advantage, particularly for short-term projections. At the same time, the differences observed here are modest, and the short horizon makes it premature to draw firm conclusions. The centrally produced forecasts are also freely available to municipalities, which may lower barriers to their use, particularly among smaller municipalities with limited analytical resources. While this accessibility is a clear advantage, it also raises concerns that municipalities relying solely on central forecasts risk losing their "projection literacy" and understanding of how demographic assumptions shape local futures. In any case, the findings underline the importance of considering not only methods and data but also institutional arrangements when evaluating the accuracy and policy relevance of population projections.

In other respects, our results align well with previous research (see literature review). For example, accuracy was found to decrease linearly with the length of the projection time, small children and young adults were the most difficult age groups to project, and migration was the demographic component with the lowest overall accuracy.

Three areas for future research stand out as particularly important. First, further comparisons of different periods in time would be welcome. Second, certainly following the present study and in the Swedish context, the vast majority of municipalities have smaller populations than those included here. Judging by the literature, these smaller municipalities are expected to have lower projection accuracy. Further research that includes a larger number of smaller municipalities in Sweden and elsewhere is needed. Third, the question of whether projection accuracy improves with greater local knowledge needs to be addressed more thoroughly, as our premature

Table 5 Comparison of mean absolute percentage error (MAPE) between statistics Sweden's (SCB) and municipal projections (total population and demographic components)

Total population		Births		Deaths		In-migration		Out-migration		Number of projections
Municipal	SCB	Municipal	SCB	Municipal	SCB	Municipal	SCB	Municipal	SCB	
Projection target year										
1 0.31	0.35	6.60	5.96	5.48	5.83	5.84	8.05	7.50	18.07	45
2 0.71	0.67	8.95	6.44	4.71	4.15	7.71	8.72	10.33	11.60	29
3 1.18	1.18	17.81	13.43	3.77	4.75	7.61	5.69	7.64	13.10	15

SCB, statistics Sweden

comparison between projections carried out by Statistics Sweden and those conducted by the municipalities, suggests that this may be the case.

Thus, while Chi and Wang (2017) concluded that more knowledge about accuracy cannot be used to improve projections (but can be used for better interpretation), our results suggest that there is potential for using local knowledge to improve projections. For example, the challenge of predicting births has, to some extent, been mitigated by obtaining data from maternity care centers (where pregnant women usually register months in advance of giving birth) in a few Swedish municipalities (see also Rayer & Smith, 2010, and Rees et al., 2019, for further examples). Nonetheless, as Hoem (1973) made clear half a century ago, some uncertainty will—by necessity—always remain, no matter how good the data and methods employed.

In conclusion, the findings of this study help reduce uncertainty surrounding expectations of population projections, benefiting both decision-makers who rely on such projections and those involved in their formulation. Overall, the results align with previous studies conducted in other countries, though the level of accuracy in the Swedish population projections analyzed here appears slightly better, with a mean absolute percentage error of 3.29% after ten years. This higher accuracy is likely attributable to the relatively large populations in the studied municipalities, the availability of current and detailed data in Sweden, and possibly the involvement of municipal officers with substantial local knowledge in conducting the projections. However, the study is limited by the small number of municipalities and the short time period under study. Thus, future research should investigate the accuracy of projections in more municipalities with varying spatial and temporal characteristics. Moreover, in a few more years, data will be available to draw reliable conclusions regarding possible systematic differences in accuracy due to the use of local knowledge.

Our findings also carry implications beyond the Swedish context. While our study is situated in Sweden, several aspects of the analysis are relevant for other countries. First, Sweden's continuous population registers make it possible to evaluate forecasts against detailed and accurate demographic information. In many other countries, evaluations must rely on decennial census counts, where both the longer time intervals and less precise base populations add to the uncertainty. Second, our evaluation is based on "real" projections that incorporate locally chosen assumptions and institutional practices, rather than on uniform applications of the same projection method across areas, which is common in the literature. This provides a closer

reflection of the conditions under which projections are actually produced and used. Third, we report accuracy not only for the total population but also for individual demographic components, and we use several error measures. This gives a more nuanced view of projection accuracy that can be informative for both researchers and practitioners. Finally, Sweden provides a rare institutional setting where centrally produced municipal forecasts coexist with local ones. This arrangement allows us to compare the two approaches directly and illustrates the potential benefits and drawbacks of centralized versus decentralized forecasting models—an issue that is highly relevant in many other countries considering how best to organize their projection systems. Taken together, our findings not only contribute to a better understanding of projection accuracy in Sweden but also provide insights of broader relevance for how population forecasts are produced, evaluated, and used in small-area contexts internationally.

Beyond its academic contribution, this study provides a practical foundation for more informed use of population projections in local policy and planning. The quantified error margins offer a concrete point of reference that has been lacking in Swedish municipal practice. While it has long been understood that projections are not exact, the absence of systematic evaluations has allowed uncertainty to be overstated or invoked selectively in political and administrative debates. By showing that projection errors are typically modest rather than extreme, this study enables planners and decision-makers to use projections with greater confidence and engage more constructively with discussions on future demand, investment, and service provision.

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Declarations

Conflict of interest The authors have no conflict of interest or competing interests.

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