



# The Future of Assisted Reproductive Technology Live Births in the United States

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## Abstract

As postponement of first births continues in the United States, women and couples will likely continue to turn to assisted reproductive technologies (ART) to overcome biological barriers to childbearing. This paper uses stochastic projections to estimate the potential impacts of ART on the US total fertility rate (TFR) overall and across sociodemographic groups using publicly available data. Assuming the trends in ART continue and the TFR remains at the mean estimate, the projection shows the ART TFR will rise from 0.023 accounting for 1.29% of the mean projected TFR in 2020 to 0.048 or 2.64% of the TFR by 2040. However, for the TFR of women over 30, this percentage is estimated at 2.68% in 2020 and 5.60% by 2040. Group-level projections quantify stratification by parity, race, and education assuming trends across these groups continue. Overall, the results show that if current trends continue, growth in demand for ART will likely increase, especially at older maternal ages, even as inequalities by race and social class remain. These projections provide a picture of ART births if inequality in access and outcomes is not addressed and highlight the need for attention to policies that address these disparities.

**Keywords** Assisted reproduction · Disparities · Stochastic projection · Infertility

## Introduction

Access and use of infertility treatments in the United States has risen steeply since the late 1980s (Kissin et al., 2016; Menken, 1985; Toner et al., 2016). Estimates from the National Survey of Family Growth have shown increases in the proportion of women aged 22–44 who have ever used assisted reproductive technologies (ARTs) since the 1990s (Stephen et al., 2016). According to the Centers for Disease Control and Prevention (CDC), ARTs are fertility treatments where eggs *and* sperm

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or embryos are handled outside of the body. This definition includes technologies such as in vitro fertilization (IVF) and its various forms, but excludes treatments such as intrauterine insemination (IUI) (Centers for Disease Control and Prevention et al. 2019). Part of the increase in ART use is likely due to greater acceptance and dissemination of these technologies (Johnson-Hanks et al., 2011).

At the same time, social and demographic factors are also likely influencing these increases. For example, Tierney and Cai (2019) show that women with a four-year degree and those with more than a four-year degree have high rates of ART births based upon population-level birth certificate data.<sup>1</sup> ART use among these women is likely the result of postponement of pregnancies and age-related infecundity. Notably, educational attainment has been rising since 2000 across the United States, with the percentage of women aged 25–29 earning a bachelor's degree or higher rising from 30% in 2000 to 42% in 2019 (National Center for Education Statistics, 2020). Projections from the National Center of Education Statistics show continued growth in the percentage of degrees conferred to women (Hussar & Bailey, 2019). Thus, it is likely that educational-related postponement will continue.

In addition, economic recessions, such as the one that may be caused by the COVID-19 pandemic, are also associated with postponement of pregnancies due to increasing college enrollment and uncertainty along with declines in income and marriage (Cherlin et al., 2013; Schneider, 2015; Sobotka et al., 2011). Postponement of pregnancy, for any reason, increases fertility issues (Dunson et al., 2004; Menken, 1985; Morgan & Rackin, 2010; te Velde, 2002) and increases the demand for ART and other infertility treatments (Leridon & Shapiro, 2017; Leridon & Slama, 2008). Together, these types of social and demographic shifts will likely increase US demand for ART in future. Although clinics and providers may see an increase in demand for ART, little or no work has attempted to quantify this growth or explore how it may unfold across sociodemographic groups in the United States.

However, future-oriented demographic analyses of ART in Europe and Australia are available. For example, cohort-based projection analyses using Danish register data predicted an increase in ART use by birth cohort from 2.1% for the oldest cohort in the study (1965) up to 7% in later birth cohorts (Sobotka et al., 2008). In addition, Raymer et al. (2020) recently used a cohort-component projection approach to estimate medically assisted births (from ART, IUI, and ovulation induction) in Australia taking into account rising educational attainment and success rates of these technologies. The study predicted ART cycles will increase between 34 and 61% by 2026, depending on model parameters of the success rates of ART, while IUI cycles and ovulation induction will decline. The study also found the share of births due to fertility treatments will grow to 8.1% of all births in the final period of their projections (2021–2026).

These findings and others (e.g., Habbema et al., 2009; Hoorens et al., 2007) suggest that the contribution of ART to total fertility is small, but substantive. If the US continues to experience declines in fertility, ART use may follow the patterns

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<sup>1</sup> In the US, a four-year degree most often corresponds with a bachelor's degree. These qualifications differ across contexts.

projected in Denmark or Australia. However, the US differs from the Danish and Australian context in several important ways. First, insurance access and coverage vary more in the US than other countries with centralized health insurance, and ART is often expensive even with insurance coverage (Katz et al., 2011; Wu et al., 2014). Second, the proportion of births due to ART is already higher in these other countries relative to the United States (Calhaz-Jorge et al., 2017; Raymer et al., 2020; Sunderam et al., 2019). Third, health disparities broadly by race and socioeconomic status are more varied in the US than many high-income peer countries (Woolf & Aron, 2013), and evidence of this stratification in outcomes from ART, number of ART births, and access to infertility treatments by race, and less commonly SES, has also been documented (e.g., Adashi & Dean, 2016; Humphries et al., 2016; Smith et al., 2011; Tierney & Cai, 2019).<sup>2</sup> Finally, although recent trends show the US total fertility rate (TFR) is declining, U.S. TFR has historically remained higher than other low-fertility, high-income countries (e.g., Hamilton et al., 2020; Morgan & Taylor, 2006). As a result, analysis of US-based data including stratified projections is needed to understand the influence of these technologies on US fertility as well as to contribute insights into the range of potential outcomes for ART globally.

Using several sources of publicly available data, the present paper uses stochastic projection methodologies to anticipate future trends in the percentage of the TFR due to ART in the United States. Given the documented racial and socioeconomic disparities in ART (e.g., Ethics Committee of the American Society for Reproductive Medicine, 2015; Humphries et al., 2016), this paper provides projections by race and education. Additionally, the results are provided by parity in order to better clarify the role of ART as a means to avoid involuntary childlessness. The results show that if current trends continue, ART will continue to play a growing, small, and uneven role in the future of US fertility. We end with a discussion of the implications of these results for researchers and policymakers.

## Data and Methods

### National Vital Statistics System (NVSS)

The NVSS birth certificate data are collected by US States and compiled by the National Center for Health Statistics (NCHS). The present analyses use these data from 2009 to 2019 to determine the number of births overall and by parity, race, and educational attainment. ART births are identified using the information reported in Box 41 of the revised 2003 birth certificate, which asks medical personnel indicate whether ART was used. The definition used for ART births for these birth certificates aligns with the definition from the CDC given above. The birth certificate data also include a separate indicator for the use of fertility drugs and IUI, which

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<sup>2</sup> Notably, SES disparities in access to ART have also been found in Australia where health care coverage is available (K. Harris et al., 2016).

are excluded from the present study. Information on ART is only publicly available beginning in 2009.

Data quality restrictions removed women with unlikely parity and age or age and educational attainment combinations. Additionally, the analyses are limited to women who reside in the United States and states that did not report infertility treatment status were excluded (2–33 states, depending on year of data). The states excluded can be found in the user guides available from the NCHS (National Center for Health Statistics, 2020).

### **Current Population Survey (CPS)**

The CPS is a publicly available nationally representative monthly survey of US households carried out by the US Census Bureau and the US Bureau of Labor Statistics (Flood et al. 2020). The CPS includes a number of periodic supplements, including a fertility and marriage supplement every other year. The present study used the 2008–2018 fertility supplements and the 2019 CPS core survey to estimate population counts by parity, race, and educational attainment. In years without a fertility supplement, linear interpolation of the population size by parity was used. The total population counts obtained using the yearly core CPS do not differ substantively from the interpolated values when summed by parity. States that do not report ART on birth certificates were excluded from population counts.

### **National Assisted Reproductive Technology Surveillance (NASS) Reports**

Federal regulations in the US require clinics performing ART cycles to report their success rates (102d Congress, 1992). These data are aggregated and publicly reported by the CDC. While the NASS reports are more complete, these data have limitations, which make them unsuitable for the main analyses. Specifically, the age categories available are irregular and often underspecified (e.g., all women under 35), information on race is unreliable (Wellons et al., 2012), and educational data are not reported. However, these data are used to perform a sensitivity analysis of the projections due to known ART underreporting in the NVSS (Cohen et al., 2014; Moaddab et al., 2016; Thoma et al., 2014; Tierney & Cai, 2019; Zhang et al., 2010).

### **Analytic Methods**

The analyses took place in a number of steps. First, using the NVSS and CPS data, single year of age-specific fertility rates (ASFRs) was calculated for the available years of data for ART births and non-ART births overall, by parity, race, and education.<sup>3</sup> Non-ART births were calculated by subtracting ART-identified births from

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<sup>3</sup> Although the CPS was used, these findings are similar to those published by Tierney and Cai (2019), who used the NVSS data and the American Community Survey to provide a description of ART births in the United States.

total births. Second, using these ASFRs, projections for 2020–2040 were computed using Lee's (1993) fertility projection model, which is an adaptation of the Lee-Carter method of mortality projection (Lee & Carter, 1992). As an extrapolation methodology, this approach bases the projection on prior trends and patterns in the historical data, and it is stochastic, meaning it incorporates random error (Booth, 2006; Lee, 1993).

The Lee (1993) method of projection (formula 1) uses observed ASFRs to fit a single-parameter that is then forecasted using a stochastic time-series model.

$$f_{x,t} = a_x + f_t \times b_x + e_{x,t} \quad (1)$$

In formula 1,  $f_{x,t}$  is the fertility rate for age  $x$  at time  $t$  (observed)—one entry in matrix  $F$ ,  $a_x$  is the mean age-specific fertility rate schedule for age  $x$  in vector  $a = (a_1, a_2, \dots, a_x)$ ,  $f_t$  indicates the change in fertility rates for time period  $t$  in vector  $f = (f_1, f_2, \dots, f_t)$  and  $b_x$  is an element of vector  $b = (b_1, b_2, \dots, b_x)$  indicating how much age group  $x$  changes as  $f_t$  changes. The error term ( $e_{x,t}$ ) captures the age-period effects not included in the model (Lee, 1993). Singular value decomposition (SVD) of the mean-centered age-specific fertility rates is carried out. From the SVD, the first right singular vector is used as a basis for  $b$  and the left singular vector is used as a basis for  $f$  by rescaling these vectors such that the first sums to zero and the second sums to one. We do not adjust for cohort tempo changes (e.g., Kohler & Ortega, 2002) nor do we make assumptions about the association between postponement and ART births.

Instead, the computation of the projections follow these steps, summarized from Lee (1993): (1) the mean ASFR is calculated from the historical data across all years under study, (2) the mean ASFR is subtracted from each individual year of observed ASFR to calculate the centralized ASFR ( $a_x$ ), (3) a SVD is computed using the centralized ASFR and is used to calculate the  $b$  and  $f$  vectors<sup>4</sup> as described above, (4) a secondary adjustment is made to  $f_t$  by using the initial model to predict the number of births and comparing this to the observed historical births and then adjusting the parameter so that the two counts match, and (5) the adjusted  $f_t$  is multiplied by  $b_x$  and is summed with the average ASFR ( $a_x$ ). The resultant matrix  $F$  containing age-specific fertility rates for age  $x$  at time  $t$  ( $f_{x,t}$ ) can then be forecasted or transformed to incorporate in constraints as Lee (1993) describes. The central advantage of this approach is that the projected TFR can also be disaggregated into ASFRs as follows from formula 1 and derived by Lee (1993).

Initial modeling used Lee's (1993) suggested transformation to constrain non-ART TFR to remain between 1.1 and 3.0; however, due to the use of a model that reverts to the mean, such constraints had little impact on the results, and were, thus, not employed in the final analyses. We also explored constraining the ART TFR to be between 0 and 0.15. If applied to the current US TFR, this ART TFR would amount for 8% of the total TFR. This value was selected based upon the observed

<sup>4</sup>  $b$  is the first principal component of  $F$  and  $f$  is a vector of the coefficients or loadings of the first principal component.

highest rates of ART births among European countries and future projections from other contexts (Calhaz-Jorge et al., 2017; Raymer et al., 2020; Sobotka et al., 2008). However, as observed in the results, the ART TFR remains below this level for all analyses. Therefore, we do not use the transformed parameter in our estimations.

Finally,  $f_{x,t}$  is fit and forecasted using an auto-regressive integrated moving average (ARIMA) model. The projection produces an estimate of the TFR, in the following formula (2):

$$TFR = A + f_t + E_t \quad (2)$$

where  $E_t$  is the sum of the errors across the different age groups, which should be close to zero, and  $A$  is the sum of  $a_x$  (Lee, 1993).

Multiple auto-regressive integrated moving average (ARIMA) models were tested for each projection. For non-ART fertility, the selected model assumes the trend will converge to the mean of the time period (ARIMA(0,0,0)).<sup>5</sup> When projecting ART fertility, we use a random-walk model with a drift (ARIMA(0,1,0)). By using these models and specifications, we assume that the ART-trend will continue in a roughly linear fashion. This assumption is motivated by the trends in ART cycles observed in previous work (Stephen et al., 2016). That is, historical data suggest that ART use has not “leveled off” and the social factors discussed in the introduction indicate continued growth. Additional details on alternative ARIMAs or other model specifications are available upon request.

To ensure our results were coherent, or consistent, across models, we use a top-down hierarchical forecasting approach to calculate projected proportions. Following Hyndman and Athanasopoulos (2018) and Athanasopoulos et al. (2009), the procedure for this approach was as follows: (1) project ART and non-ART births and subgroups independently, (2) sum the forecasts for each category of groups to create non-coherent TFR for each year of the projection, and (3) multiply these proportions by the overall forecast.

The analyses were repeated across parity, race, and educational groups using the procedures above and employing this top-down reconciliation approach to ensure the results were coherent for each set of projections. These analyses were completed using the “demography,” “forecast,” and “fable” packages in R (Hyndman, 2019; Hyndman et al., 2020; O’Hara-Wild & Hyndman, 2021). Importantly, the prediction intervals for reconciled forecasts remains an open area of inquiry, which means the prediction intervals provided should be treated with caution (Hyndman et al., 2011; Panagiotelis et al., 2020, 2021; Wickramasuriya et al., 2019). However, to provide more information about potential pathways of the overall forecast, we identify two scenarios that combine the mean TFR projection with the upper 80% prediction

<sup>5</sup> The assumption of reverting to the mean is consistent with Lee’s (1993) work and represents a realistic and straightforward possible scenario, though alternative approaches may be more accurate (Bohk-Ewald et al., 2018). Lee (1993) uses an ARIMA(1,0,1) model. However, the use of an ARIMA(0,0,0) minimizes the AICc and fits our time series better than the ARIMA(1,0,1). This divergence from Lee (1993) may be the result of the shorter and less stable fertility data used in these analyses.

interval of the ART TFR (Scenario 1) and with the lower 80% prediction interval of the ART TFR (Scenario 2) for reference.

## Supplemental and Sensitivity Analyses

Several supplemental and sensitivity analyses are provided to contextualize these results. First, we use Lee's (1993) method to show the predicted ASFR due to ART to provide more information about how these models predict ART to change over time. In addition, we use these ASFRs to calculate the predicted TFR for women over 30 overall and due to ART to provide an estimate of how ART contributes to TFR at older ages. These results, however, should be treated with caution as the reconciliation for coherent forecasts only occurs at the aggregate level.

In addition to these supplementary analyses, we provide two sensitivity analyses for our results. First, given the known underreporting of ART in the NVSS data (Cohen et al., 2014; Moaddab et al., 2016; Thoma et al., 2014; Tierney & Cai, 2019; Zhang et al., 2010), analyses were conducted using counts of ART births extracted from the CDC's public reports of the NASS data. Specifically, using the CDC's reports, the number of ART births to women in the following age groups was extracted for 2009–2018: under 35, 35–37, 38–39, and 40–42, and over 43. For the unconstrained ages, we assume under 35 includes women 30–35 and women over 43 includes women 43–49. Making this assumption, we carry out the analyses as described above.

A second sensitivity test concerns the independent estimation of non-ART and ART birth rates to estimate the percentage of the TFR due to ART. To address the interrelation between overall fertility and ART fertility, we also forecast overall and ART fertility parameters using a vector auto-regressive model (VAR) rather than the ARIMA forecasting model employed in the main analyses. VAR models are recursive and allow for the inclusion of lagged past values of both the series itself and other covariates (Hyndman & Athanasopoulos, 2018). We use this approach to incorporate lagged values of the ART parameter to predict future values of the overall fertility parameter, and vice versa. To carry out the VAR analyses, we follow the procedures outlined by Hanck and colleagues (2020), and we use the “vars” package in R (Pfaff, 2008). We specifically use a VAR(2) as a two-year lag had the lowest AIC of the available lags. The series are not cointegrated, thus, we do not use the vector error correction model (VECM). Further details of this robustness test are available upon request.

## Results

### Overall Projected Impact of ART

In the mean projections, we observe an increase in the ART TFR from 0.023 (80% Prediction Interval: 0.022–0.025) in 2020 to 0.048 (80% PI: 0.045–0.050) (Table 1). In terms of percentages, the mean ART model predicts 1.29% of the projected mean

**Table 1** Projected ART TFR with 80% prediction intervals and the percentage of the projected TFR due to ART with alternative scenarios based on 80% prediction intervals of ART TFR by parity, race, and educational attainment for selected years

	2020	2025	2030	2035	2040
Overall					
Projected TFR (80% Prediction Interval) <sup>a</sup>	1.800 (1.700–1.900)	1.800 (1.700–1.900)	1.800 (1.700–1.900)	1.800 (1.700–1.900)	1.800 (1.700–1.900)
Projected ART TFR (80% Prediction Interval) <sup>a</sup>	0.023 (0.022–0.025)	0.029 (0.028–0.031)	0.035 (0.034–0.037)	0.042 (0.039–0.044)	0.048 (0.045–0.050)
Percentage of the TFR due to ART (Scenario 1, Scenario 2) <sup>b</sup>	1.29% (1.22%, 1.37%)	1.63% (1.54%, 1.73%)	1.97% (1.86%, 2.08%)	2.31% (2.18%, 2.44%)	2.64% (2.49%, 2.79%)
Parity <sup>c</sup>					
Parity 1 Projected ART TFR	0.0083 (0.0079–0.0088)	0.0106 (0.0100–0.0111)	0.0128 (0.0121–0.0135)	0.0149 (0.0141–0.0158)	0.0171 (0.0162–0.0180)
% of Group-Specific Projected TFR due to ART	1.44% (1.36%, 1.52%)	1.82% (1.72%, 1.92%)	2.20% (2.08%, 2.32%)	2.57% (2.43%, 2.71%)	2.95% (2.78%, 3.11%)
Parity 2 Projected ART TFR	0.0069 (0.0065–0.0073)	0.0087 (0.0082–0.0092)	0.0105 (0.0099–0.0110)	0.0122 (0.0116–0.0129)	0.0140 (0.0132–0.0148)
	1.36% (1.28%, 1.43%)	1.71% (1.62%, 1.81%)	2.06% (1.95%, 2.18%)	2.41% (2.28%, 2.54%)	2.76% (2.61%, 2.91%)
Parity 3 Projected ART TFR	0.0038 (0.0036–0.0040)	0.0047 (0.0045–0.0050)	0.0057 (0.0054–0.0060)	0.0066 (0.0063–0.0070)	0.0076 (0.0071–0.0080)
	1.13% (1.07%, 1.20%)	1.42% (1.35%, 1.50%)	1.71% (1.62%, 1.80%)	2.00% (1.89%, 2.11%)	2.28% (2.16%, 2.40%)
Parity 4 + Projected ART TFR	0.0044 (0.0041–0.0046)	0.0055 (0.0052–0.0058)	0.0067 (0.0063–0.0071)	0.0079 (0.0074–0.0083)	0.0090 (0.0085–0.0095)
	1.14% (1.08%, 1.21%)	1.45% (1.37%, 1.53%)	1.76% (1.66%, 1.86%)	2.06% (1.95%, 2.18%)	2.37% (2.24%, 2.50%)
Race/Ethnicity <sup>c</sup>					
Black, NH, Projected ART TFR	0.0020 (0.0019–0.0021)	0.0026 (0.0025–0.0028)	0.0033 (0.0031–0.0034)	0.0039 (0.0037–0.0041)	0.0045 (0.0043–0.0048)
	0.55% (0.52%, 0.58%)	0.72% (0.68%, 0.76%)	0.89% (0.84%, 0.94%)	1.07% (1.01%, 1.12%)	1.24% (1.17%, 1.30%)
White, NH, Projected ART TFR	0.0058 (0.0055–0.0061)	0.0072 (0.0068–0.0076)	0.0086 (0.0081–0.0091)	0.0086 (0.0081–0.0091)	0.0113 (0.0107–0.0120)
	1.73% (1.63%, 1.82%)	2.14% (2.02%, 2.26%)	2.56% (2.42%, 2.70%)	2.97% (2.80%, 3.13%)	3.38% (3.19%, 3.56%)
Hispanic, Projected ART TFR	0.0022 (0.0020–0.0023)	0.0028 (0.0027–0.0030)	0.0035 (0.0033–0.0037)	0.0042 (0.0039–0.0044)	0.0048 (0.0046–0.0051)
	0.50% (0.48%, 0.53%)	0.66% (0.62%, 0.70%)	0.82% (0.77%, 0.86%)	0.97% (0.92%, 1.02%)	1.13% (1.06%, 1.19%)
Asian/NHOPI, NH, Projected ART TFR	0.0076 (0.0072–0.0080)	0.0097 (0.0091–0.0102)	0.0117 (0.0111–0.0124)	0.0137 (0.0130–0.0145)	0.0157 (0.0148–0.0166)

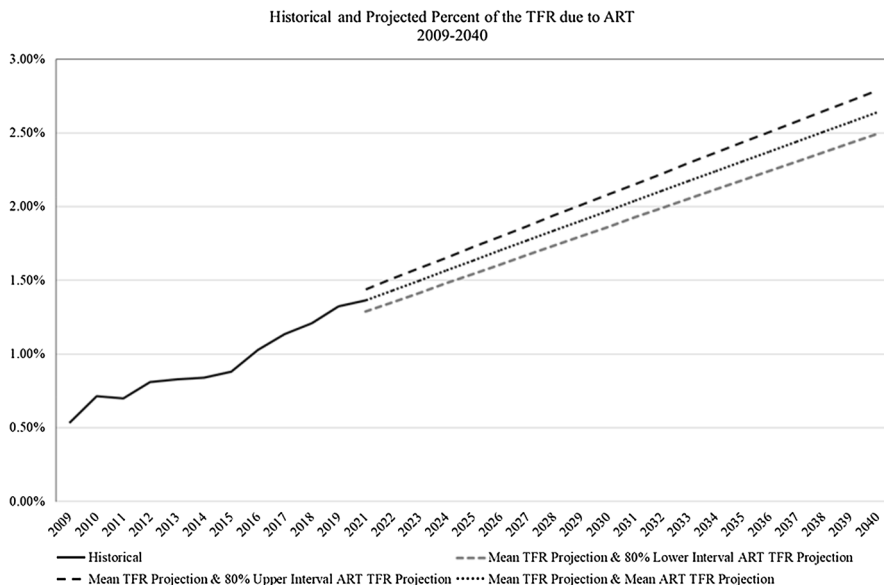


Table 1 (continued)

	2020	2025	2030	2035	2040
Other Race, NH, Projected ART TFR	2.33% (2.20%, 2.46%) 0.0046 (0.0044–0.0049) 1.35% (1.28%, 1.43%)	2.96% (2.79%, 3.12%) 0.0059 (0.0056–0.0062) 1.73% (1.63%, 1.82%)	3.58% (3.38%, 3.78%) 0.0072 (0.0068–0.0076) 2.10% (1.98%, 2.22%)	4.19% (3.96%, 4.43%) 0.0085 (0.0080–0.0089) 2.47% (2.33%, 2.61%)	4.80% (4.53%, 5.07%) 0.0097 (0.0092–0.0103) 2.84% (2.68%, 2.99%)
Educational Attainment <sup>c</sup>					
Less than BA, Projected ART TFR	0.0039 (0.0037–0.0041) 0.56% (0.53%, 0.59%)	0.0050 (0.0047–0.0052) 0.71% (0.67%, 0.75%)	0.0060 (0.0057–0.0063) 0.86% (0.81%, 0.91%)	0.0071 (0.0067–0.0075) 1.01% (0.96%, 1.07%)	0.0081 (0.0077–0.0086) 1.16% (1.10%, 1.23%)
BA, Projected ART TFR	0.0116 (0.0110–0.0123) 2.21% (2.08%, 2.33%)	0.0140 (0.0132–0.0148) 2.66% (2.51%, 2.81%)	0.0163 (0.0154–0.0173) 3.11% (2.93%, 3.28%)	0.0187 (0.0176–0.0197) 3.55% (3.35%, 3.75%)	0.0210 (0.0198–0.0222) 3.99% (3.77%, 4.21%)
More than BA, Projected ART TFR	0.0202 (0.0191–0.0213) 3.51% (3.31%, 3.70%)	0.0245 (0.0231–0.0258) 4.25% (4.02%, 4.49%)	0.0287 (0.0271–0.0303) 4.98% (4.71%, 5.26%)	0.0328 (0.0310–0.0347) 5.70% (5.39%, 6.02%)	0.0369 (0.0349–0.0390) 6.41% (6.06%, 6.77%)

<sup>a</sup> As discussed in the text, 80% prediction intervals may be unreliable in reconciled forecasts and should be treated with caution  
<sup>b</sup> Scenario 1 combines the mean TFR projection with the Lower 80% Prediction Interval estimate of the ART TFR; Scenario 2 combines the mean TFR projection with the Upper 80% Prediction Interval estimate of the ART TFR

<sup>c</sup> For the Parity, Race, and Educational Attainment, estimates of the percentage of the TFR due to ART use the group-specific projected TFRs  
 ART Assisted Reproductive Technology, TFR Total Fertility Rate, NH Non-Hispanic, NHOPI Native Hawaiian or Pacific Islander, BA Bachelor's Degree

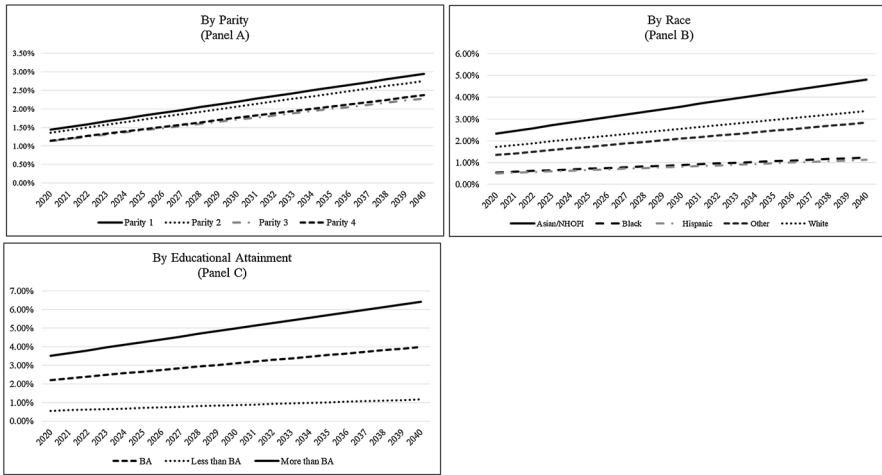


**Fig. 1** Observed and projected percent of the overall TFR due to ART 2009–2040 with alternative scenarios. *ART* Assisted Reproductive Technology, *TFR* Total Fertility Rate, *NVSS* National Vital Statistics System. The two scenarios presented are based upon the 80% prediction interval estimates for the ART TFR. However, as discussed in the text, 80% prediction intervals may be unreliable in reconciled forecasts and should be treated with caution

TFR will be due to ART in 2020 and will increase to 2.64% by 2040. If the ART TFR follows the upper bound of the prediction interval and the TFR remains as the mean projection, 1.37% of the TFR will be due to ART in 2020 and 2.79% of the TFR will be due to ART in 2040. By contrast, if the ART TFR follows the lower bound of the prediction interval and the TFR remains at the mean projection, 1.22% of the TFR will be due to ART in 2020 and 2.49% of the TFR will be due to ART in 2040. Figure 1 displays the historical and projected percentage of the TFR due to ART along with the projected path assuming the ART TRF follows the bounds of the prediction interval and the TFR remains at the mean projection (scenario 1 and 2).

### Group-Level Projections: Parity, Race, and Education

Table 1 includes the ART TFR mean and upper and lower 80% prediction intervals along with the estimated percentage of the group-specific TFR due to ART for selected years. Figure 2 illustrates the percentage of the projected group-specific TFR due to ART by parity (Panel A), race/ethnicity (Panel B), and educational attainment (Panel C). In Table 1 and Fig. 2, Panel A, we observe the percentage of the parity-specific TFR due to ART across parities. The results show continued growth in the percentage of the TFR due to ART for all parities. The parity-specific TFR due to ART is highest



**Fig. 2** Projected percentage of the group-specific TFRs due to ART 2020–2040 by parity (Panel A), race/ethnicity (Panel B), and education (Panel C). *ART* Assisted Reproductive Technology, *TFR* Total Fertility Rate, *NHOPI* Native Hawaiian or Other Pacific Islander, *BA* Bachelor’s Degree. Calculations use the mean ART and TFR projections within each group

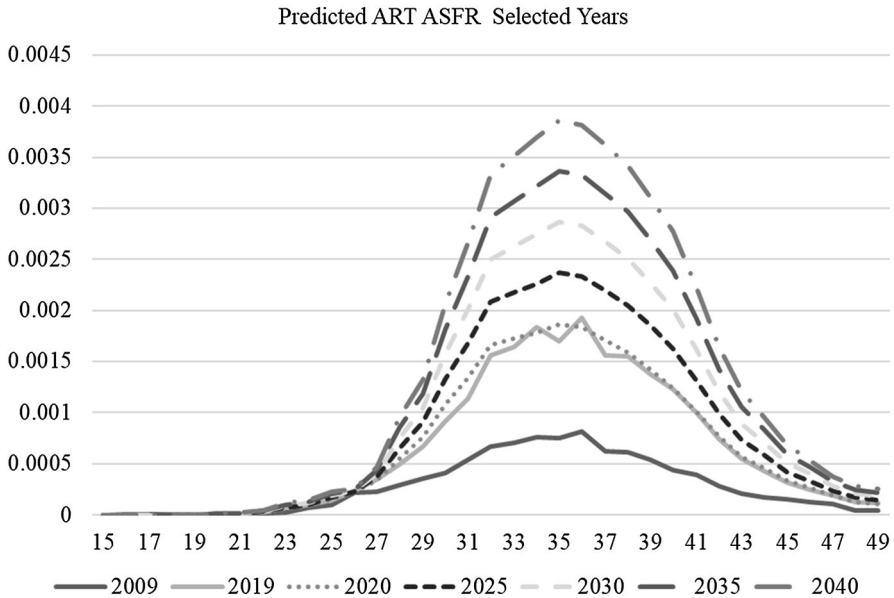
for parity 1 and parity 2 births, with ART comprising 2.95% and 2.76% of parity 1 and parity 2 TFRs, respectively, by 2040. Parities 3 and 4+ are similarly grouped at lower levels with the mean model estimating that ART will comprise 2.28% and 2.37% of each of the parity-specific TFRs, respectively, by 2040.

In Fig. 2, Panel B, we observe inequalities in the percentage of births due to ART across racial groups. The percentage of the TFR for Black women due to ART and the TFR for Hispanic women due to ART are projected to remain below 1.5% for the entire projection period (1.24% and 1.13% in 2040, respectively). Meanwhile, the percentage of the group-specific TFRs due to ART is highest among Asian/NHOPI women and White women, with estimates of 4.80% of the TFR and 3.38% of the TFR being due to ART in 2040 for each group. ART births to women of other races are also projected to increase, with 2.84% of the TFR due to ART by 2040.

In Fig. 2, Panel C, educational stratification is evident. Throughout the projection period, the percent of the TFR for women with a four-year degree due to ART increases to 6.41% of births by 2040. Similarly, the percentage of the TFR due to ART of women with a four-year degree is projected to increase to 3.99% in 2040. The percentage of the TFR due to ART for women less than 4-year degree is projected to increase from 0.56% of the group TFR in 2025 to 1.16% of the group-TFR in 2040.

**Supplemental Analyses**

Figure 3 provides a graph of the ART ASFRs for selected years in the projection. We observe ART births as concentrated among women over 30 and younger than 45. Using the projected ASFRs, we calculated the ART and overall TFR for women



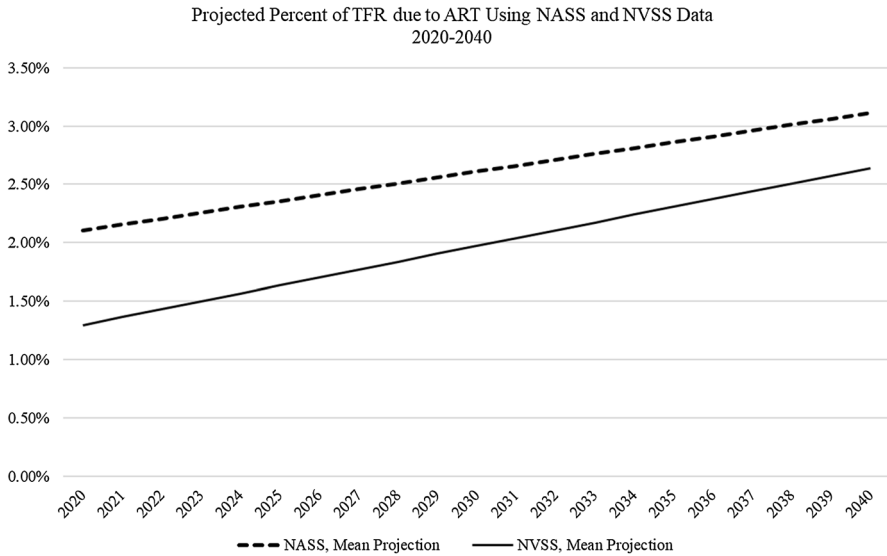
**Fig. 3** ART ASFRs for selected historical and projected years. *ART* Assisted Reproductive Technology, *ASFR* Age-specific Fertility Rates

over 30 for selected years. In 2020, the overall TFR for women over 30 was 0.79 and the ART TFR for women over 30 was 0.021 and for 2040, the overall TFR remained at 0.79 per the model assumptions, while the ART TFR rose to 0.044. Combining these estimates of the TFR for women over 30, the mean projections show that in 2020, 2.68% of the TFR to women over 30 would be attributed to ART and by 2040 5.60% of the TFR for women over 30 would be due to ART.

### Sensitivity Analyses

Across the projection period, we observe the NVSS model underestimates the percentage of the overall TFR due to ART (Fig. 4). The NASS model predicts that by 2040, 3.11% of the TFR will be due to ART. The ART TFR for 2040 is estimated at 0.059 (80% PI: 0.053–0.064), which is considerably higher than the NVSS projection (Table 1), though these intervals should be treated with caution. Overall, the NASS model predicts a higher proportion of the TFR due to ART, yet both models suggest less than 3.5% of the TFR will be due to ART by 2040.

In the VAR estimated projections, the projection of overall TFR is lower than the main projections as we do not assume it reverts to the mean in this model. As a result, the percentage of the TFR due to ART is higher across the projection (Fig. 5, Panel A). Importantly, the ART TFR in the VAR model is slightly lower than the NVSS estimates, though the prediction intervals do overlap (Fig. 5, Panel B). Thus,



**Fig. 4** Percentage of the TFR due to ART 2020–2040 based on NASS and NVSS mean projections. *ART* Assisted Reproductive Technology, *TFR* Total Fertility Rate, *NASS* National ART Surveillance System, *NVSS* National Vital Statistics System

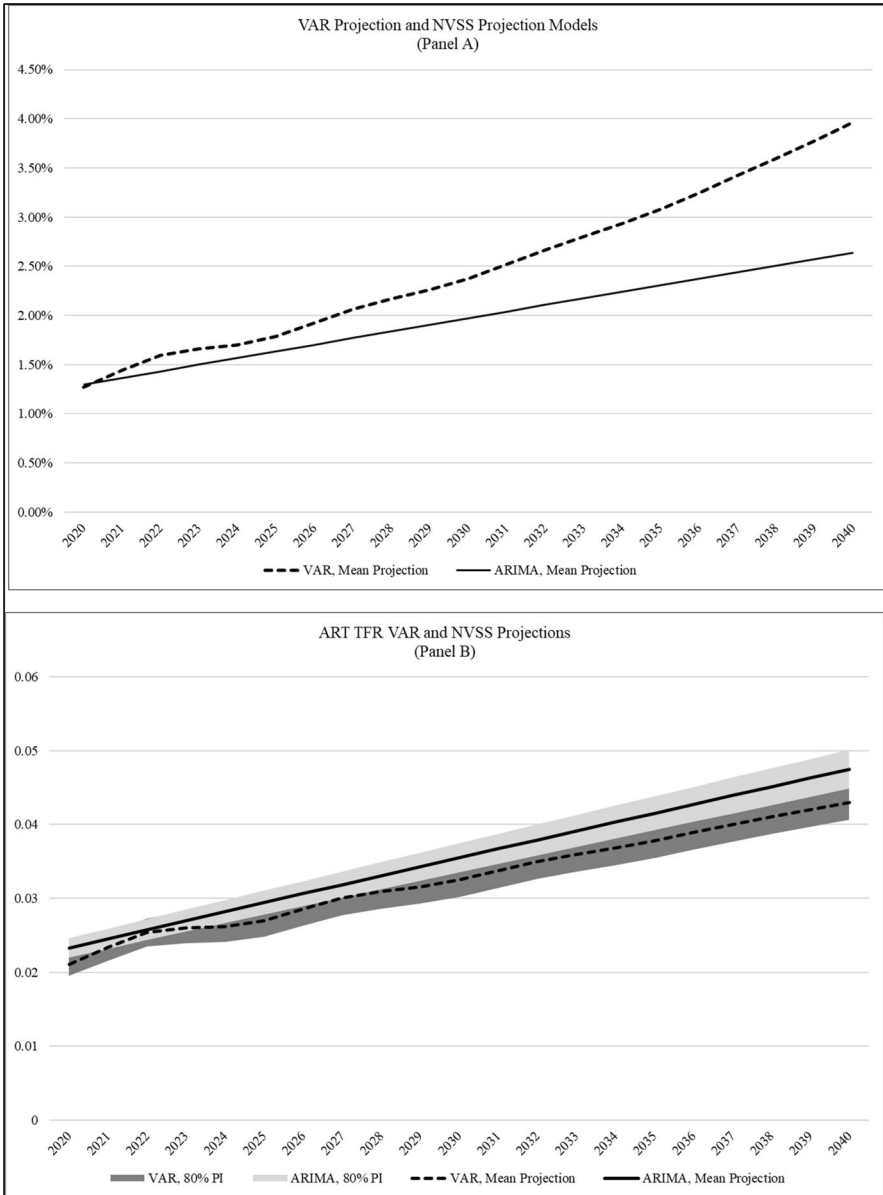
the differences in the percentage of the TFR are mostly due to the differences in the overall TFR projection.

## Conclusion

This paper projects the potential future impacts of ART on TFR overall and across sociodemographic groups in the United States if current trends continue. The projections characterize the future impact of ART on US fertility as growing, small, and unequal. If no interventions are enacted to improve equity in ART access, utilization, or outcomes, and trends continue, US ART births will remain concentrated among groups with economic and social advantages as seen in the projections.

The mechanisms of stratification in ART birth rates require further investigation. Prevalence rates of infertility show either no race and education differences or show those with the lowest ART use have a higher prevalence of infertility issues (Chandra & Stephen, 2010; Chandra et al., 2013; Peck et al., 2016). These findings suggest that differential need for services is not a compelling cause of the inequalities observed. Unfortunately, demographic data are unable to clarify the mechanisms of inequality further.

When considering these projections, two sets of limitations should be noted. First, projections are sensitive to model assumptions and parametrization and cannot account for all possible outcomes. Our projection includes implicit and explicit assumptions about the future of ART, which influence our results. For example, we assume the ART TFR will continue based on prior trends and will progress in a



**Fig. 5** Percentage of the TFR due to ART from the VAR and ARIMA Models (Panel A) and the ART TFR with 80% Prediction Intervals from the VAR and ARIMA Models (Panel B). *ART* Assisted Reproductive Technology, *TFR* Total Fertility Rate, *ARIMA* Autoregressive integrated moving average, *VAR* Vector Autoregression, *PI* Prediction Interval. As discussed in the text, 80% prediction intervals may be unreliable in reconciled forecasts and should be treated with caution

relatively linear manner. As a result, our results show continued and small growth in ART and reflect the trends in stratification by parity, race, and education that exist in the available data.

Whether these assumptions of linear growth and continued subgroup trends are accurate is not known. It is plausible that the ART birth rates may increase more sharply or that the trend may behave in a curvilinear fashion within the forecasting horizon. Indeed, if access issues and inequalities are addressed, our results would likely underestimate the proportion of the TFR due to ART as well as potentially overstate the inequalities across racial and educational groups. Interestingly, however, research on insurance mandates has demonstrated that increases in ART births generally remain concentrated among White and high-SES women, which may suggest that access alone would be insufficient to drastically change stratification in ART births without other interventions in place (Bitler & Schmidt, 2012). Relatedly, the projections do not address other potentially impactful social, policy, and demographic contexts such as the effects of COVID-19 on demand, changing ART success rates, or changing educational attainment. These factors were outside of the scope of our analyses. Thus, our prediction model presents one potential future of ART if the trends continue as we have specified.

A second set of limitations is related to the quality and availability of data. For example, there are relatively few years of NVSS data on ART births, making more detailed projections difficult. Additionally, the NVSS data are known to underestimate ART births (Cohen et al., 2014; Moaddab et al., 2016; Thoma et al., 2014; Tierney & Cai, 2019; Zhang et al., 2010). However, the sensitivity analyses conducted with the NASS data contextualize this issue. Another limitation of the available data is the inability to address state variation in use (Harris et al., 2017; Sunderam et al., 2019) or differing utilization patterns among foreign-born women (Levine et al., 2017).

Given the limitations of this paper, it is clear there remain important avenues for future research. First, counterfactual analyses addressing the different trends in ART under different total fertility, social, and policy contexts would be fruitful for understanding the other potential pathways this technology may take. Second, as more US ART data become available, researchers could follow Raymer and colleagues' (2020) work on Australian data and use a cohort-component method that explicitly addresses changes in educational attainment, mean age at first birth, and changing success rates of ART. Third, extending these analyses by assessing race and educational patterns jointly for US data would be particularly useful in forecasting how racial disparities in ART may unfold. Notably, trends in educational attainment among Black and Hispanic populations, generally, and among Black and Hispanic women show increases in educational attainment, which could lead to an increase in ART use that is not accounted for in our projections (Everett et al., 2011; McDaniel et al., 2011; National Center for Education Statistics 2020, 2021; US Census Bureau, 2022). That is, if educational attainment among these populations continues to increase, we would also expect postponement and, thus, increases in ART use. Recent projections from the National Center for Education Statistics predict an 8% and 14% increase in Black and Hispanic students enrolled in secondary-degree granting universities between 2017 and 2028 (Hussar & Bailey, 2020). Clearly, such

analyses also have great potential to help identify the mechanisms through which this stratification occurs. Finally, scholars that have access to restricted-use data that include information on state and nativity could carry out projections using this information, which would provide a more nuanced picture of the future of ART across the United States.

Despite these limitations and need for continued research, the results of this paper have implications for US policymakers. Specifically, continued advocacy for mandated insurance coverage for infertility treatments is a necessary approach to lessen the cost-related barriers to use of ART. In addition to standardizing and expanding coverage among private insurers, Medicaid coverage should also be expanded to improve reproductive equity. While addressing cost barriers is an important first step in ameliorating disparities, others have noted this is not the only barrier (Chin et al., 2015; Greil et al., 2011; Janitz et al., 2016). Thus, other policy interventions are also needed. For example, postponement of births is often related to the conflict between family and work policies (McDonald, 2006; Mills et al., 2011). As a result, scholars have suggested that family leave and other policies that make it easier to have children when desired need to be pursued (Mills et al., 2011). Ultimately, equity in infertility care will require coordinated and focused efforts that address both proximate and distal causes.

Although these results will likely differ from those of other countries due to the political, social, and health context of the United States, these findings reinforce prior work demonstrating the impacts of ART on fertility for policymakers outside of the United States. Specifically, the small proportion of births projected to be attributable to ART if trends continue in the US is largely consistent with work from scholars in lowest–low fertility contexts, which conclude that ART alone is not a solution for low fertility (Blyth & Lee, 2013; Habbema et al., 2009, 2015; Hoorens et al., 2007; Kocourkova et al., 2014; Sobotka et al., 2008). Thus, policymakers in these contexts should continue to evaluate alternative policies that enable people to have the families they want and/or to consider how immigration policies can address the social and economic impacts of lowest–low fertility.

Although the future contribution of ART is likely small in the US and other countries, it may be the difference between having desired biological children and being involuntarily childless for some. Paired with social and demographic trends, the results show how demand for ART may increase in the United States if current trends continue in the coming years. It is not yet known whether policy or practice will grow equitably with these changes. However, as more people seek these services, attention to inequalities must remain central to policymakers in order to ensure reproductive equity consistent with calls from the CDC (Center for Disease Control & Prevention, 2014) and the American Society for Reproductive Medicine (Ethics Committee of the American Society for Reproductive Medicine, 2015).

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**Data Availability** The data underlying this article are derived from sources in the public domain: NVSS data are available from the CDC ([https://www.cdc.gov/nchs/data\\_access/vitalstatsonline.htm](https://www.cdc.gov/nchs/data_access/vitalstatsonline.htm)), CPS data are available from IPUMS (<https://cps.ipums.org/cps/>), external estimates of the projected population and age-specific fertility rates are available from US Census Bureau (<https://www.census.gov/programs-surveys/popproj.html>), and external counts of ART births can be found in the reports located on the CDC's ART website (<https://www.cdc.gov/art/reports/archive.html>).

**Code Availability** The Stata and R coding used for these analyses are available upon request. The paper makes use of the publicly available “forecast” package in R (Hyndman et al., 2020) and the “vars” package in R (Pfaff, 2008).

## Declarations

**Conflict of Interest** The author has no conflict of interest to declare.

**Ethical Approval** This study was deemed exempt from IRB review by the University of North Carolina at Chapel Hill's institutional review board.

**Additional Declarations for Articles in Life Science Journals That Report the Results of Studies Involving Humans and/or Animals** Not applicable.

**Consent to Participate** Not applicable.

**Consent for Publication** Not applicable—sole author.

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