Original Research Article

The Influence of Birth Season on Mortality in the United States

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Objectives: Birth season is related to a variety of later outcomes. Among them, mortality is of great interest because it represents lifetime health outcomes. We examined the relationship between birth season and mortality in the US.

Methods: We merged the US National Health Interview Survey (NHIS) and NHIS public-use linked mortality files and analyzed 17,082 men and 19,075 women who were followed for 20 years from 1986 to 2006. We used the Cox proportional hazards model to relate birth quarter to mortality, controlling for birth year fixed effects.

Results: After controlling for years of schooling and birth year fixed effects, we found that, relative to men born in the first quarter, men born in the fourth quarter were 11% less likely to die. For women, the benefit was the largest for women born in the third quarter who were 14% less likely to die than women born in the first quarter. In the relationship between birth season and mortality, cardiovascular diseases played a noticeable role for men and malignant neoplasms for women.

Conclusions: These results were consistent with those for some developed countries, but not entirely with those for contemporary developing countries and developed countries of the past. Simple mechanisms based on the perinatal environment cannot account for the inconsistent results. We suggest that family background may play some, but not an exhaustive, role in the relationship between birth season and mortality. Am. J. Hum. Biol. 28:662–670, 2016. © 2016 Wiley Periodicals, Inc.

A large body of research in the social and natural sciences has demonstrated that birth season is related to a variety of outcomes, including height, test performance, wages, educational attainment, schizophrenia, autism, dyslexia, extreme shyness, suicide risk, self-reported luckiness, the likelihood of being left-handed, and mortality (Buckles and Hungerman, 2013; Sohn, 2015). Among these outcomes, mortality is of great interest because it represents lifetime health outcomes.

Researchers studying the relationship between birth season and mortality have considered both developing and developed countries and have typically drawn on early life conditions to explain their results. As explained in the discussion section, however, these results often conflict with each other even for countries that share similar climates and income levels. In addition, although these studies heavily relied on prenatal and early postnatal events to explain the relationship, evidence suggests that these events may not play a major role in the relationship (Buckles and Hungerman, 2013). Instead, family background appears to play a more powerful role, at least in the US. That is, birth season is not randomly distributed, but women with better adult outcomes (e.g., marital status, education, and income) avoid winter births more effectively. Therefore, children born in seasons other than winter exhibit better outcomes (e.g., test performance, wages, and educational attainment) than those born in winter.

In this literature for developed countries, the study of Dobhlhammer and Vaupel (2001) is exemplary. They considered individuals aged 50+ in Denmark, Austria, and Australia. The data were nationally representative, the observation numbers were large (1,371,003 for Denmark, 681,677 for Austria, and 219,820 for Australia), and the follow-up period was long particularly for Denmark (1968–1998 for Denmark, but 1988–1996 for Austria and 1993–1997 for Australia). Using the high-quality datasets, they estimated the deviation in the remaining lifespan of people born in specific months from the average remaining lifespan at age 50, and found that in Denmark and Austria (the Northern Hemisphere) adults born in the second half of the year lived longer than those born in the first half. The same seasonal patterns emerged for Australia (the Southern Hemisphere), with a half-year shift.

No study has elaborated the relationship between birth season and mortality in the contemporary US. Costa and Lahey (2003) predicted 10-year mortality rates for Americans aged 60–79 in 1960–1980, but only in passing. Because the US shares a similar climate to Denmark, Austria, and Australia, one may presume that it would exhibit similar patterns. This presumption is too hasty, however, because the results for Denmark, Austria, and Australia do not agree with those for Greece (Doblhammer and Vaupel, 2001; Flouris et al., 2009). In addition, studies for developing countries suggest that a simple extrapolation is naive because even areas that are close in distance exhibited sometimes dramatically different patterns in the relationship. Neither do studies using US historical data agree with each other (Costa and Lahey, 2003; Huntington, 1938; Su, 2009). Furthermore, the importance of family background, instead of perinatal environment, for the US implies that we need to revisit the mechanisms that have been proposed in the literature.

This investigation is also worthy because it provides results relevant to the present time. Individuals in Doblhammer and Vaupel's data were too old to provide insights into the health of contemporary populations. Danes were at least 50-years old on April 1, 1968, the starting point of follow-up. This means that they were born in 1918 or earlier. In the 20th century, the improvement in medical technology...
was astounding, to say the least. In 1900–1937, the US crude mortality rate for infectious diseases decreased by ~2.8% per year, which was facilitated indirectly by the germ theory of disease and directly by public health interventions, such as clean water supply and improved sanitation (the First Mortality Revolution). This downward trend was accelerated by a wave of medical innovations in the 1940s (the Second Mortality Revolution), so the mortality rate declined by 8.2% per year in the subsequent 15 years. At present, chronic diseases are major threats to life, but the lives of patients with major chronic diseases can be sustained through current medical technology. The relationship between obesity (a major health threat) and mortality illustrates this point well. The relationship has weakened over time (Mehta and Chang, 2011), and now obesity is more likely to shorten disability-free life expectancy than overall life expectancy at middle and older ages (Reuser et al., 2009); to wit, obesity does not kill but disables. Moreover, death rates from cardiovascular diseases already started to decline in 1950 thanks to pharmaceutical innovations, improved effectiveness of invasive medical treatments, and behavioral changes. Among the leading causes of death, only cancer is elusive to treatment now, despite the century-long effort (Mukherjee, 2010). Thus, the disease environment faced by the Danes is much different from that experienced by people in developed countries at present. The same arguments apply to the studies by Huntington (1938), Costa and Lahey (2003), and Su (2009). We addressed this concern by following individuals aged 18+ in 1986 until 2006.

This study has other advantages over previous studies. All studies for developing countries, to the best of our knowledge, have analyzed data from small areas, thereby weakening their abilities to generalize the results. We addressed this limitation by analyzing a nationally representative sample. Related to this issue, some studies for developing countries have drawn on samples of small size, thus decreasing their estimation precision. Therefore, it is difficult to determine whether statistically nonsignificant, but large in magnitude, estimates truly indicate no relationship or merely a false negative. We tackled this limitation by using large sample sizes: 17,082 men and 19,075 women. Furthermore, follow-up periods in previous studies were often short. In contrast, we followed the same people for up to 20 years. The issues of small sample size and short follow-up period were addressed in some studies using historical data for developed countries (Gagnon, 2012; Gavrilov and Gavrilova, 1999; Huntington, 1938, ch. 8; Su, 2009). We addressed this concern by following individuals aged 18+ in 1986 until 2006.

Because the number of non-whites in the data was not large enough for a precise estimation, we considered only whites. And we considered only adults, i.e., people aged 18+. When we controlled for education, however, we restricted ages to 25+ to allow time to complete a college education. By examining adults, we might introduce selection bias. For example, children born in a certain season survived better, and they might bias the influence of the season on mortality. However, survival causes two opposing biases. A strong child survives, but so does a scarred child. A child is scarred when life conditions were harsh, not enough to kill him but nevertheless enough to weaken him. A strong child may bias the influence of the season on mortality upward, but the scarred one downward. A priori, it is difficult to know which is greater. If they cancel each other, selection in this study was not critical.

Because birth information was self-reported, measurement error was of potential concern. We initially considered birth month and eventually birth quarter. We argue that measurement error was probably a minor concern because, although respondents might be unsure of their birth days, they could correctly recall birth months and years, particularly in this highly literate population. We simplified the classification of seasons as follows: the first birth quarter corresponds to winter, the second to spring, the third to summer, and the fourth to autumn. One could object that winter should correspond to not the first quarter but December in the previous year and January and February in this year—the other seasons follow thereafter. This classification maybe suitable for a country of small size. However, the US land area is vast, and consequently, there is no one-size-fits-all matching between months and seasons. Winter may start in December in some states, and January in others. That said, we showed that the difference of 1 month between the alternative and ours was not important by analyzing data after equally dividing January–December into halves and thirds. Furthermore, our classification was helpful in

**DATA AND METHODS**

We combined two datasets: the National Health Interview Survey (NHIS) and NHIS public-use linked mortality files. The survey is nationally representative, covering the civilian noninstitutionalized population residing in the US at the time of the interview. It is a cross-sectional household interview survey, and the sampling plan follows a multistage area probability design, which permits the representative sampling of households and noninstitutional group quarters. The survey primarily collects information on current health, so retrospective demographic information is limited. The National Center for Health Statistics updated the mortality linkage of the NHIS for 1986–2004 to death certificates found in the National Death Index. The most up-to-date follow-up period is dated to December 31, 2006, and death date is available in quarters. Although the NHIS is a cross-sectional survey, by merging the two datasets, we could create a longitudinal dataset. We selected the 1986 NHIS to obtain the longest possible follow-up period. Sohn (forthcoming) used the same scheme to show that the taller died earlier.

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TABLE 1. Descriptive statistics

<table>
<thead>
<tr>
<th>Continuous variable</th>
<th>Men</th>
<th>Women</th>
</tr>
</thead>
<tbody>
<tr>
<td>Birth quarter</td>
<td>Mean (SD)</td>
<td>Mean (SD)</td>
</tr>
<tr>
<td>3rd quarter in 1942</td>
<td>12.6 (3.3)</td>
<td>12.2 (3.0)</td>
</tr>
<tr>
<td>3rd quarter in 1940</td>
<td>12.6 (3.3)</td>
<td>12.2 (3.0)</td>
</tr>
<tr>
<td>Age</td>
<td>43.2 (17.4)</td>
<td>45.2 (18.5)</td>
</tr>
<tr>
<td>Years of schooling*</td>
<td>12.6 (3.3)</td>
<td>12.2 (3.0)</td>
</tr>
<tr>
<td>Discrete variable</td>
<td>%</td>
<td>%</td>
</tr>
<tr>
<td>Birth month</td>
<td></td>
<td></td>
</tr>
<tr>
<td>January</td>
<td>8.26</td>
<td>8.39</td>
</tr>
<tr>
<td>February</td>
<td>7.68</td>
<td>7.74</td>
</tr>
<tr>
<td>March</td>
<td>8.45</td>
<td>8.40</td>
</tr>
<tr>
<td>April</td>
<td>7.74</td>
<td>7.59</td>
</tr>
<tr>
<td>May</td>
<td>7.93</td>
<td>7.81</td>
</tr>
<tr>
<td>June</td>
<td>8.29</td>
<td>8.18</td>
</tr>
<tr>
<td>July</td>
<td>8.61</td>
<td>8.68</td>
</tr>
<tr>
<td>August</td>
<td>9.55</td>
<td>8.54</td>
</tr>
<tr>
<td>September</td>
<td>9.03</td>
<td>8.56</td>
</tr>
<tr>
<td>October</td>
<td>8.66</td>
<td>7.78</td>
</tr>
<tr>
<td>November</td>
<td>7.66</td>
<td>8.05</td>
</tr>
<tr>
<td>December</td>
<td>8.14</td>
<td>8.27</td>
</tr>
<tr>
<td>Dead due to accidents</td>
<td>25.68</td>
<td>23.37</td>
</tr>
<tr>
<td>Otherwise</td>
<td>74.32</td>
<td>76.63</td>
</tr>
<tr>
<td>Dead due to malignant neoplasms</td>
<td>6.40</td>
<td>5.57</td>
</tr>
<tr>
<td>Otherwise</td>
<td>93.60</td>
<td>94.43</td>
</tr>
<tr>
<td>Dead due to cardiovascular diseases</td>
<td>10.80</td>
<td>10.19</td>
</tr>
<tr>
<td>Otherwise</td>
<td>89.20</td>
<td>89.81</td>
</tr>
<tr>
<td>Dead due to accidents</td>
<td>1.54</td>
<td>0.72</td>
</tr>
<tr>
<td>Otherwise</td>
<td>98.46</td>
<td>99.28</td>
</tr>
<tr>
<td>N</td>
<td>17,104</td>
<td>19,082</td>
</tr>
</tbody>
</table>

Notes: *ages were restricted to be 25+, and the sample size was 14,506 for men and 16,484 for women. SD stands for standard deviation.

discussing our results because Buckles and Hungerman (2013) provided important insights and they used the same classification as ours.

The variable of years of schooling was also self-reported, and we entered this variable as a continuous one. A small number of respondents failed to report the number of years in college. We recorded their years of schooling as 14 years. Although this variable was not of major interest in this study, in preliminary analysis, we experimented with a categorical variable, with 0 indicating 11 years of schooling or less and 1 indicating 12 years of schooling or more. The transformation did not change the substance of the results (not shown).

The literature on mortality typically uses the Cox proportional hazards model, so we also used this model. We subsequently employed similar models to determine whether or not the results derived from the Cox model were driven by the specific model. We applied sampling weights to make the estimates nationally representative. The variable of interest was birth month and eventually birth quarter; we briefly considered half year and third year. It is possible that patterns of birth quarter changed over time in a fashion related to mortality. In this case, birth year confounds the relationship between birth quarter and mortality. To examine this, we regressed birth year on a series of dummies for birth quarters by sex, but all coefficients were not statistically significant for either sex (not shown). Thus, controlling for birth year would make little difference to the hazard ratios for birth quarters. Nevertheless, we controlled for birth year fixed effects, which controlled for all factors common to the same birth year. In other words, we compared the influence of birth quarter on mortality for individuals born in the same year (i.e., within birth year comparisons).

Main results

Figure 1 presents the hazard ratios for birth months by sex, after controlling for birth year fixed effects. January is the reference month, and capped spikes represent the 95% confidence intervals. As the confidence intervals indicate, the hazard ratios for all birth months (except August for women) were not statistically significant. However, some general patterns emerge from the figure: men and women born in the second half of the year exhibited a lower chance of dying than those born in the first half.

This method differs from controlling for a linear term of birth year, which compares individuals born in all birth years (i.e., between birth year comparisons). The within specification is more robust than the between specification because the between specification controls for only a linear trend of mortality and fails to control for factors that deviate from the trend. We intentionally controlled for only birth year fixed effects—and years of education as a robustness check—because our aim was to estimate the total effect of birth season on mortality.

We began our analysis with deaths owing to all causes, and later we separately considered deaths owing to the two leading causes of death in the US. The NHIS comprises 113 causes of death listed in the International Statistical Classification of Diseases and Related Health Problems, 10th Revision (ICD-10). In the ICD-10, malignant neoplasms in the NHIS correspond to C00–C97, and cardiovascular diseases to I00–I99. For a robustness check, we also excluded non-disease related deaths, which correspond to V01–Y88.

We excluded 29 men and women who died in the quarter of the interview, which left us with 17,082 men and 19,075 women in our sample. Table 1 presents the descriptive statistics.

RESULTS

We used a Cox proportional hazards model and applied sampling weights. Lines indicate hazard ratios. Capped spikes indicate the 95% confidence intervals. *: P value<0.05.
equality and similar tests rejected the null hypothesis that the two lines were the same.

Figures 1 and 2 motivated us to more formally analyze the relationship between birth season and mortality. Table 2 presents the hazard ratios for birth quarters and education. Panel A concerns men and Panel B women. When only birth quarter was controlled for (Column 1), in general men born in the first quarter exhibited the highest chance of dying. Relative to them, men born in the third quarter exhibited a 10.7% lower chance of dying; this corresponds to the upper panel of Figure 2. When we added birth year fixed effects (Column 2), the hazard ratio for the third quarter slightly increased from 0.893 to 0.914 but remained statistically significant. The hazard ratio for the fourth quarter decreased from 0.934 to 0.893 and turned statistically significant: relative to men born in the first quarter, men born in the fourth quarter exhibited a 10.7% lower chance of dying.

Recall that our interest was to estimate the total effect of birth season on mortality, so the results in Column 2 constitute our main results. However, Buckles and Hungerman (2013) highlighted the importance of family background in the relationship between birth season and adult outcomes. We checked whether this was true in our case. Because the NHIS is a cross-sectional survey and questions related to family background are rare, we were forced to use only education as a proxy for it. Nevertheless, this variable should capture a non-negligible influence of family background on mortality because family background exerts a powerful influence on education—more than school resources do (Björklund and Salvanes, 2011).

When we added years of schooling, the hazard ratio for education indicates that an additional year of schooling was related to a 4.1% lower chance of dying. More importantly, all birth quarters changed little after controlling for education, suggesting that family background proxied by education does not play a great role in the relationship between birth season and mortality. Nevertheless, the hazard ratio for education offers an intuitive understanding of the size of the influence of birth season on mortality. The hazard ratio for the third quarter (0.912), as presented in Column 3, suggests that being born in the third quarter decreased the chance of dying as much as did about two additional years of schooling. Being born in the fourth quarter exerted an even greater influence.

The results for women were slightly different from those for men. For example, when only birth quarter was controlled for (Column 1), the hazard ratios for the third and fourth quarters were statistically significant, whereas the hazard ratio only for the third quarter was statistically significant for men. When we added birth year fixed effects (Column 2), the hazard ratio for the fourth quarter lost statistical significance, whereas the opposite was the case for men. As a result, the third quarter exhibited the lowest chance of dying for women, whereas the fourth quarter did for men. The size of the relationship between birth quarter and mortality in Column 2 also differed between the two sexes to a noticeable degree: women born in the third quarter showed a 14.6% lower chance of dying than those born in the first quarter; the corresponding figure for men was 8.6%. That said, the general patterns were similar between the two sexes. Individuals born in the second half of the year experienced a lower chance of dying than those born in the first half, and family background proxied by education played a modest role in mediating the relationship between birth season and mortality.

It could be that the Cox proportional hazards model artificially drove the results, so we employed other models with a natural proportional hazards parameterization. We excluded education from the model, but including it was immaterial (not shown). Table 3 lists the results when the survival distribution was exponential, Gompertz, and Weibull. Irrespective of the survival distribution, the main message remained the same. That is, individuals born in the second half of the year faced a lower chance of dying than those born in the first half, and the decreasing effect was more pronounced for the fourth quarter for men and for the third quarter for women.

Tables 2 and 3 suggest that it is meaningful to categorize individuals by half birth year. We combined the first and second quarters to constitute the first half of the birth year and the third and fourth quarters to constitute the second half. When we replaced quarter with half year in the Cox model (Panel A of Table 4), men born in the second half of the year exhibited a 10.5% lower chance of dying than those born in the first half; the corresponding figure for women was 8.8%. We repeated the exercise after replacing half year with third year (Panel B). The first third year consisted of January–April, the second May–August, and the third September–December. Men born in the last third year exhibited a 7.8% lower chance of dying than those born in the first third year. The corresponding figure for women was almost the same. Interestingly, women born in the second third year exhibited the smallest chance of dying, which is consistent with the importance of the third quarter for women. In any case, Tables 2–4 confirm that, however we divided the year, men and women born early in the year were likely to die earlier than those born later in the year, and the difference in the change was not small.

Additional results

Thus far, our assumption has been that mortality is largely driven by disease, and this assumption rests on the literature about the relationship between birth season and mortality. If the relationship is driven by nondisease such
as accidents and suicide, we need to revisit the literature. This is particularly the case because seasonality has been observed in accidents and suicide (Buckles and Hungerman, 2013). We checked whether this underlying assumption was valid by excluding deaths caused by nondisease. Column 1 of Table 5 shows that the exclusion made little difference to the main results (Column 2 of Table 2), particularly for women.

In Columns 2 and 3, we investigated whether the relationship was driven by certain diseases. Unfortunately, the sample size was not large enough to consider finely defined diseases, so we limited our attention to the two leading causes of death in the US: malignant neoplasms and cardiovascular diseases. We repeated the Cox model, considering deaths owing to these two causes, instead of deaths owing to all causes. Column 2 suggests that relative to men born in the first quarter, those born in the second quarter exhibited a 19.4% higher chance of dying of malignant neoplasms, but men born in the third and fourth quarters did not exhibit a higher chance of dying. This is not entirely consistent with our main results, suggesting that malignant neoplasms may not be the main driving force behind the relationship between birth season and mortality. When we considered cardiovascular diseases, however, we could replicate the patterns seen in our main results, implying that cardiovascular diseases may play an important role in the relationship.

Interestingly, these results differed from those for women. The hazard ratios for birth quarters for malignant neoplasms were more consistent with our main results; that is, women born in the third quarter faced a lower chance of dying than those born in the first quarter. The hazard ratios for all birth quarters for cardiovascular diseases were not statistically significant. This does not appear to be produced

### Table 2. Relationship between birth quarter and mortality

<table>
<thead>
<tr>
<th></th>
<th>1</th>
<th>2</th>
<th>3</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A: Men</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2nd Qtr.</td>
<td>0.966 (0.886, 1.053)</td>
<td>1.021 (0.939, 1.112)</td>
<td>1.006 (0.924, 1.096)</td>
</tr>
<tr>
<td>3rd Qtr.</td>
<td>0.893 (0.820, 0.972)*</td>
<td>0.914 (0.839, 0.995)*</td>
<td>0.912 (0.837, 0.993)*</td>
</tr>
<tr>
<td>4th Qtr.</td>
<td>0.934 (0.857, 1.018)</td>
<td>0.893 (0.819, 0.974)*</td>
<td>0.890 (0.816, 0.972)*</td>
</tr>
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<td>Years of schooling</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Birth year fixed effects</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>N</td>
<td>17,082</td>
<td>17,082</td>
<td>14,487</td>
</tr>
<tr>
<td><strong>Panel B: Women</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2nd Qtr.</td>
<td>0.934 (0.857, 1.018)</td>
<td>0.941 (0.862, 1.027)</td>
<td>0.949 (0.869, 1.037)</td>
</tr>
<tr>
<td>3rd Qtr.</td>
<td>0.853 (0.784, 0.928)*</td>
<td>0.854 (0.785, 0.930)*</td>
<td>0.859 (0.789, 0.935)*</td>
</tr>
<tr>
<td>4th Qtr.</td>
<td>0.903 (0.829, 0.982)*</td>
<td>0.919 (0.843, 1.002)</td>
<td>0.926 (0.848, 1.010)</td>
</tr>
<tr>
<td>Years of schooling</td>
<td></td>
<td></td>
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<tr>
<td>Birth year fixed effects</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>N</td>
<td>19,075</td>
<td>19,075</td>
<td>16,477</td>
</tr>
</tbody>
</table>

Notes: We used a Cox proportional hazards model and applied sampling weights. Hazard ratios are listed. Age was restricted to 18+ for Columns 1 and 2 and 25+ for Column 3. The first quarter is the reference group. 95% confidence intervals are in parentheses. *: P value < 0.05.

### Table 3. Relationship between birth quarter and mortality: parametric survival models

<table>
<thead>
<tr>
<th></th>
<th>Exponential</th>
<th>Gompertz</th>
<th>Weibull</th>
</tr>
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<tbody>
<tr>
<td><strong>Panel A: Men</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2nd Qtr.</td>
<td>1.018 (0.945, 1.098)</td>
<td>1.021 (0.938, 1.112)</td>
<td>1.024 (0.941, 1.113)</td>
</tr>
<tr>
<td>3rd Qtr.</td>
<td>0.928 (0.861, 1.001)</td>
<td>0.913 (0.838, 0.994)*</td>
<td>0.917 (0.843, 0.997)*</td>
</tr>
<tr>
<td>4th Qtr.</td>
<td>0.909 (0.843, 0.982)*</td>
<td>0.892 (0.818, 0.973)*</td>
<td>0.895 (0.821, 0.975)*</td>
</tr>
<tr>
<td>Birth year fixed effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>N</td>
<td>17,082</td>
<td>17,082</td>
<td>17,082</td>
</tr>
<tr>
<td><strong>Panel B: Women</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2nd Qtr.</td>
<td>0.939 (0.871, 1.013)</td>
<td>0.941 (0.861, 1.028)</td>
<td>0.943 (0.866, 1.028)</td>
</tr>
<tr>
<td>3rd Qtr.</td>
<td>0.865 (0.804, 0.931)*</td>
<td>0.853 (0.784, 0.929)*</td>
<td>0.858 (0.789, 0.932)*</td>
</tr>
<tr>
<td>4th Qtr.</td>
<td>0.930 (0.864, 1.002)</td>
<td>0.919 (0.843, 1.003)</td>
<td>0.922 (0.847, 1.003)</td>
</tr>
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<td>Birth year fixed effects</td>
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<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>N</td>
<td>19,075</td>
<td>19,075</td>
<td>19,075</td>
</tr>
</tbody>
</table>

Notes: We applied sampling weights. Hazard ratios are listed. The first quarter is the reference group. 95% confidence intervals are in parentheses. *: P value < 0.05.

### Table 4. Relationship between half or third birth year and mortality

<table>
<thead>
<tr>
<th></th>
<th>1</th>
<th>2</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2nd half year</td>
<td>0.895 (0.842, 0.950)*</td>
<td>0.912 (0.857, 0.969)*</td>
</tr>
<tr>
<td>3rd half year</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2nd third year</td>
<td>0.963 (0.895, 1.036)</td>
<td>0.903 (0.837, 0.973)*</td>
</tr>
<tr>
<td>3rd third year</td>
<td>0.922 (0.856, 0.994)*</td>
<td>0.923 (0.857, 0.994)*</td>
</tr>
<tr>
<td>Birth year fixed effects</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>N</td>
<td>17,082</td>
<td>19,075</td>
</tr>
<tr>
<td><strong>Panel B</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2nd half year</td>
<td></td>
<td></td>
</tr>
<tr>
<td>3rd half year</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2nd third year</td>
<td></td>
<td></td>
</tr>
<tr>
<td>3rd third year</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Notes: We used a Cox proportional hazards model and applied sampling weights. Hazard ratios are listed. The reference group is the first half year for Panel A and the first third year for Panel B. 95% confidence intervals are in parentheses. *: P value < 0.05.
by a smaller number of deaths owing to cardiovascular diseases (i.e., false negatives) because the number of deaths owing to cardiovascular diseases was 1,945, whereas that from malignant neoplasms was 1,062. However, as far as the sizes of the hazard ratios for birth quarters were concerned, they were close to those of our main results. At this point, we cannot assess, with confidence, the role of cardiovascular diseases in the relationship between birth season and mortality for women.

**DISCUSSION**

Using a nationally representative survey, we estimated the relationship between birth season and mortality in the US. The results suggest that men and women born in the second half of the year lived longer than those born in the first half. The benefit was pronounced for the fourth quarter for men and the third quarter for women. We also demonstrated that these main results were robust to changes in empirical models and to excluding deaths owing to nondisease. The results from further analyses suggest that in the relationship between birth season and mortality, cardiovascular diseases played a noticeable role for men and malignant neoplasms for women.

Our findings are consistent with those of Dobhammer and Vaupel (2001), but not entirely with those of Flouris et al. (2009). Flouris et al. (2009) found that Greek citizens born in December–February and September–November lived the longest. One way to reconcile the inconsistencies could be that the Greek timing of seasonal changes in health-related environmental conditions differs from the other countries. It is, however, unclear why this is the case when we observed similar results in countries with varying latitudes—from Denmark to Australia. Another way could be that Flouris et al. (2009) designated winter as December–February instead of January–March as in this study. If being born in December greatly reduces mortality and being born in January and February is weakly related to mortality, their results would agree—that being born later in the year reduces mortality. Their study cannot answer this question, and Dobhammer and Vaupel (2001) and we did not observe the assumed patterns in our studies.

Although the results were not entirely consistent, Dobhammer and Vaupel (2001) and Flouris et al. (2009) explained their results by drawing on the perinatal environment. The inconsistencies in their results, however, cast doubt on the explanations. Our review of studies for developing countries increased this doubt. For example, Moore et al. (1997) collected detailed records of births and deaths in three rural subsistence-farming villages (Keneba, Kantong Kunda, and Manduar) in the Gambia and showed that from the age of 15, individuals born in the hungry season (wet season and the second half of the year) had a greater mortality rate than those born in the harvest season (dry season and the first half of the year). They explained this finding based on David Barker’s influential hypothesis (Barker, 1998). That is, the wet season coincided with an annual hungry period when staple foods from the previous harvest were depleted. Furthermore, during this season, adults, including pregnant women, are engaged in intensive agricultural work, and infectious diseases abound. Therefore, prenatal and early postnatal events adversely affected the future health of the Gambian respondents. Because almost all causes of death resulted from acute infectious diseases, they contended that the reason for the relationship was that malnutrition during the hungry season weakened the immune system of fetuses and neonates. Therefore, they applied Barker’s original idea for chronic degenerative disease in later life to acute infectious disease. When Moore et al. (1999) extended the follow-up period, they found a greater (slightly less than three times) relationship between birth season and mortality.

Jaffar et al. (2000) repeated Moore et al.’s analysis with data collected from another region of the Gambia, Upper River Division. They found that the neonatal mortality rate (death within 28 days) was lower for neonates born in the harvest season than for those born in the hungry season (35.1 vs. 40.0, P = 0.04). However, the results were inconclusive for other age groups (29 days to 11 months of age, 12–23 months, 24–35 months, 36–47 months, and 48–59 months). Similarly, Simondon et al. (2004) collected data from Niakhar, Senegal, 140 km north of Keneba, the Gambia. They found that the risk of death was slightly greater for infants (aged 0–1) born in the hungry season than for those born in the harvest season. The mortality ratio was 1.18, with a 95 confidence interval of 1.05–1.30. However, they failed to find any statistically significant differences for the age groups 1–5 years and 5–14.5 years. In addition, Kynast-Wolf et al. (2006) considered Burkina...
Faso, which shares a similar climate to Gambia. They also found that only among infants (<age 1), mortality rates exhibited a significant heterogeneity by birth month, with the highest rates occurring in September, December, and January. The mortality patterns by birth month for all other age groups appeared to be random.

These findings are not entirely consistent with Moore et al.'s argument that the mortality difference by birth season appeared only from the age of 15 (Moore et al., 1997, 1999). Furthermore, when Moore et al. (2004) examined Bangladesh, which also exhibits wet and dry seasons, they found that being born during the hungry season resulted in excess mortality during the first year of life. This is consistent with the findings of the previous paragraph, but they found no difference by birth season in mortality beyond 15 years of age, which does not agree with their original argument (Moore et al., 1997, 1999).

The relationship becomes more complicated when these results are compared with those from aristocratic families born in Europe in 1800–1880. Their nutritional conditions probably fall somewhere between contemporary populations in the developing world and those in the developed world. Gavrilov and Gavrilova (1999) controlled for a variety of variables and estimated two (rather than one) peaks in the lifespan of adult women. Compared with women born in August, women born in May had a lifespan that was longer by 3.61 years and women born in December by 3.21 years; both were statistically significant. The finding of two peaks cannot be plausibly explained by malnutrition during the prenatal and early postnatal periods. In Europe in the past, May was a hungry season, although it is unclear whether the aristocratic families underwent the seasonal pattern of nutrition.

We could ignore the inconsistent results between ours, Dobhlammer and Vaupel's (2001) and Flouris et al.'s (2009), saying that they concerned different countries, so results could differ. Considering only US data, however, does not make matters simpler. When Costa and Lahey (2003) analyzed Union Army veterans (mostly born in the early nineteenth century), they found that those born in the fourth quarter lived the longest. Using the same data, Su (2009) extended the analysis to show that the pattern emerged only when the mean age increased from 70 to 78. This pattern was weak before and after this period, and it is unclear why the pattern manifested itself only during the short period. Huntington (1938, ch. 8) considered distinguished Americans (mostly born in the early nineteenth century) and about 80 families listed in genealogical books (unspecified but should be born much earlier than the publication year 1938) and found that, in general, people born between January and April lived the longest.

We suspect that these inconsistent results partly stemmed from the small size, unrepresentativeness, or selectivity of samples. Small sample sizes reduce estimation precision and sometimes cause a false negative. When samples are collected from unrepresentative or selective sources, even if estimation is precisely done, the results may be idiosyncratic. Furthermore, the results for contemporary developing countries and developed countries of the past may not be directly relevant to the contemporary US population because income levels are substantially different.

If it is true that the hungry season harms fetuses or neonates and they die earlier, then this pattern should be consistent. It can be accepted that this pattern is not observed in some places, but the fact that the opposite patterns occurred makes the explanation unconvincing. Even if this explanation is correct, the contradiction implies that more than one mechanism is involved in the relationship between birth season and mortality. Dobhlammer and Vaupel's (2001) and Flouris et al.'s (2009) studies are relevant to this study because they used relatively recent data for developed countries. The inconsistent results, however, make their explanations less convincing.

Researchers often neglect the fact that fetuses are resilient to adverse shocks, unless shocks are severe as in the Dutch famine during the Second World War. For example, the mean birthweight was reduced only by 51 g when fetuses during the first trimester were hit by a ruinous earthquake with a magnitude of 7.9 on the moment-magnitude scale in Chile (Torche, 2011). Terror caused by landmine explosions during the first trimester reduced birthweight by 7.8 g (Camacho, 2008). Even a thousand pounds of air developmental toxicants per square mile reduced birthweight only by 2.9 g (Currie and Schmieder, 2009). One can get a sense of the practical insignificance of the reductions by comparing them to what Black et al. (2007) found in Norwegian twins. They found that it took as much as a 10% increase in birthweight to reduce 4.1 deaths per 1,000 births. Costa and Lahey (2003, p. 132) were also skeptical of the perinatal environment story, pointing out that live birthweights remained roughly constant over the twentieth century while mortality rates declined fast. In addition, the perinatal environment story would be more convincing if conceptions were random, which has been long known not to be the case (Cowgill, 1966).

We do not deny that the perinatal environment regarding climates and their derivatives (e.g., agricultural workload, nutrition, and disease) might play a role in other countries at present and in the past. However, the perinatal environment consists of too many factors to identify the mechanisms behind the relationship between birth season and mortality. As seasons change, naturally, climatic conditions change. For example, winter is typically characterized by low levels of sunshine duration and intensity, temperature, infectious disease burden, and, depending on the region, precipitation, and consequently, humidity. As seasons change, human behavior changes, too. For example, people are more sedentary in winter than in summer (O'Connell et al., 2014). Seasons are not a destiny, either. People react to seasonal changes. In winter, for instance, people make themselves warm, and vice versa in summer. Therefore, even when one finds some correlation between climatic conditions and mortality, this does not much explain the relationship between birth season and mortality. For example, when Flouris et al. (2009) found a correlation between air temperature and mortality, we do not know whether their seasonality in mortality was driven by air temperature or its correlates, such as sunshine duration, sedentariness, and heating.

Regardless, for the contemporary US, it is difficult to maintain that the perinatal environment plays a major role because the US has been a highly urbanized country. In 1940, around the mean birth year of our sample, 56.5% of the US population already resided in urban areas, and, thereafter, the rate monotonically increased to 80.7% in 2010. Seasonality in agricultural workload is unlikely to be important. Furthermore, the US has led international trade (including food) (Findlay and O'Rourke, 2007)—certainly...
when our sample were born and growing up—and witnessed a rapid development of a distribution system (the first Walmart opened in Rogers, Arkansas, in 1962). Thus, seasonality in food availability had probably almost disappeared when the individuals in our sample were born and growing up. When taking into account the development in medical technology in the 20th century, seasonality in disease burden does not appear to be a plausible explanation for our findings. Furthermore, if the perinatal environment is a major factor, we would expect the relationship between birth season and mortality to decrease over time since seasonality in many factors related to the perinatal environment weakened. Dobihammer and Vaupel (2001) suspected this when they interpreted their results of greater seasonality for older people. They did not compare the same country over time; however, they compared different countries during different periods. We compared US results over time. According to Costa and Lahey (2003), the difference in hazard ratios was 0.105 between the second and fourth quarters while our corresponding difference was 0.116. Different covariates were controlled for, but the increase is far from what one expects from the perinatal environment story.

Buckles and Hungerman (2013) provided an alternative explanation. They analyzed the Natality Detail Files 1989–2001 and the decennial Census data for 1960–1980, thereby collecting information on the family backgrounds of children born in the US in 1945–2001. They found that relative to children born in the first quarter, those born in the rest of the year were more likely to have mothers who were better educated (i.e., had high school diplomas), married, white, and not poor. The size of the discrepancies was small, but it grew over time. For example, relative to children born in the first quarter in the 1960 census, those born in the second quarter were 0.98% more likely to have mothers with high school diplomas. The figure increased to 1.05% in the 1989–2001 Natality data. They subsequently demonstrated that controlling for family background reduced the relationship between birth quarter and later outcomes regarding education and income by 25%–40%. Eventually, they showed that the seasonality in maternal characteristics could be traced to the success of timing births. That is, married women (presumably having higher education and income levels) were more successful at timing births than single women, and they tended to avoid winter births.

Given these pieces of evidence, it seems that in the US, family background plays an important role in the relationship between birth season and mortality. If the climate plays a role, it is a relatively small one. If it ever exerts non-negligible effects on the relationship, it may do so in an indirect way by inducing families with better resources to avoid winter births.

That said, we cannot emphasize this reason too much for two reasons. First, when we controlled for years of schooling, the hazard ratios for birth quarters hardly changed. This strategy was similar to that of Buckles and Hungerman (2013). Of course, the variable of years of schooling does not capture all information on family background. However, Gagnon (2012) also found that controlling for family background did not eliminate seasonality in longevity; thus, our variable may not be too inaccurate. Given the close relationship between education and family background, if family background exerts a substantial influence on the relationship, it would decrease the hazard ratios for birth quarters to a noticeable degree. The fact that this does not warn against placing too much emphasis on family background as the main mechanism behind the relationship between birth season and mortality. Second, according to Buckles and Hungerman (2013), children born in the second quarter had mothers who had the best characteristics, not those born in the third or fourth quarter. However, when they examined later outcomes without family background being controlled for, it was children born in the third or fourth quarter who exhibited the best outcomes. The relationship between birth season and later outcomes is consistent with our mortality results, but the relationship between birth season and maternal characteristics is not. Therefore, we speculate that family background plays some role in the relationship between birth season and mortality, but it is unclear how family background exerts influence on the relationship. We have to resolve that much of the relationship is determined by factors other than family background. Nevertheless, our results regarding the two leading causes of death suggest promising paths for future research. It would be beneficial to elaborate the relationship between birth season and cardiovascular diseases for men and between birth season and malignant neoplasms for women. At the same time, it would be helpful to determine why each relationship differs by sex.

It is likely that other mechanisms are behind the relationship between birth season and mortality, and it is a critical limitation that we do not know what they are at this moment. However, we have contributed to the literature by showing the relationship for the contemporary US. Furthermore, by comparing our results with others, we have pointed out some problems with previous explanations and proposed helpful paths for future research. A second limitation is that the follow-up period was 20 years, so the majority of deaths were not observed. If all deaths had been observed, our results might have been different. However, this follow-up period was long compared to those of other studies. Furthermore, if all death cases had been observed that study would have been a historical one, thereby losing relevance in the current period. This is certainly a tradeoff, and we believe that timeliness is more important than completeness. Third, we examined only two leading causes of death. This is related to the second limitation because there were not many deaths to analyze for each cause of death. Fourth, we considered only individuals of non-Hispanic European descent because of the second limitation. African-Americans and Hispanics may experience a different relationship between birth season and mortality, and an investigation into this would enrich our understanding of the relationship.

ACKNOWLEDGMENTS

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LITERATURE CITED

