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RESEARCH ARTICLE

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Estimation of differential occupational risk of COVID-19 by comparing risk factors with case data by occupational group

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Abstract

Background: The disease burden of coronavirus disease 2019 (COVID-19) is not uniform across occupations. Although healthcare workers are well-known to be at increased risk, data for other occupations are lacking. In lieu of this, models have been used to forecast occupational risk using various predictors, but no model heretofore has used data from actual case numbers. This study assesses the differential risk of COVID-19 by occupation using predictors from the Occupational Information Network (O*NET) database and correlating them with case counts published by the Washington State Department of Health to identify workers in individual occupations at highest risk of COVID-19 infection.

Methods: The O*NET database was screened for potential predictors of differential COVID-19 risk by occupation. Case counts delineated by occupational group were obtained from public sources. Prevalence by occupation was estimated and correlated with O*NET data to build a regression model to predict individual occupations at greatest risk.

Results: Two variables correlate with case prevalence: disease exposure ($r = 0.66$; $p = 0.001$) and physical proximity ($r = 0.64$; $p = 0.002$), and predict 47.5% of prevalence variance ($p = 0.003$) on multiple linear regression analysis. The highest risk occupations are in healthcare, particularly dental, but many nonhealthcare occupations are also vulnerable.

Conclusions: Models can be used to identify workers vulnerable to COVID-19, but predictions are tempered by methodological limitations. Comprehensive data across many states must be collected to adequately guide implementation of occupation-specific interventions in the battle against COVID-19.

KEYWORDS

COVID-19, infection control, occupational medicine, preventive medicine, workplace safety

1 | INTRODUCTION

The global coronavirus disease 2019 (COVID-19) pandemic continues to have profound and devastating effects world-wide. As of this writing (August 2020), there have been over five million infections caused by the severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) virus and over 170,000 deaths in the United States alone.[1] Both on the individual and societal levels, no dimension of modern life has been spared from the impact of COVID-19 and the measures implemented in the fight against its spread.[2]

As in other pandemics, the burden of disease is not uniform across subpopulations.[3] Workers bear a particular risk of exposure during these times. Staying at home has been shown to reduce infection rates,[4] but despite the efforts of numerous industries to transition their employees

Abbreviations: BLS U.S., Bureau of Labor Statistics; CDC, Centers for Disease Control and Prevention; CI, confidence interval; COVID-19, coronavirus disease 2019; HCW, healthcare worker; O*NET, Occupational Information Network; PR, prevalence ratio; SOC, Standard Occupational Classification.

to remote work, those employed in many essential occupations do not enjoy this luxury.[5] This creates a differential risk of exposure by occupation. Although it is well known that frontline healthcare workers (HCW) are at increased risk "due to close personal exposure to patients with the virus,"[6] data for other professions, particularly in nonhealthcare industries, are sparse. In the United States, the only published statistics detailing COVID-19 infections by occupation was released in June 2020 and updated in July by the Washington State Department of Health.[7]

Due to this paucity of actual data, statistical models have been used to forecast the risk of contracting COVID-19 by occupation using various predictors. A widely cited article in the New York Times[8] identified two factors that may increase this risk: the general risk of disease exposure on the job and the physical proximity of workers to others. The author used corresponding datasets from the Occupational Information Network (O*NET) provided by the US Department of Labor, an established method of risk assessment in the occupational medicine literature.[9] Consisting of "detailed occupational information on over 900 jobs… O*NET provides estimates for workers' exposure to a number of physical hazards and adverse working conditions."[10] However, no research has correlated these factors to actual data on COVID-19 infections. The aim of this study is to identify possible predictors in the O*NET database that differ by occupation using real case numbers and to use these predictors recursively on O*NET data to forecast specific occupations at highest risk.

2 | MATERIALS AND METHODS

2.1 | Dataset selection

The present study is a retrospective analysis of preexisting occupational data to determine the differential risk of COVID-19 by profession. A recently released reported from the Washington State Department of Health detailing the absolute number of infections by major occupational group was used.[7] This report provides data on 26,799 laboratory confirmed cases of COVID-19 amongst Washington State residents up until June 16th 2020. Those cases with occupational data available (41% of the total, or 10,850) were delineated into the 22 nonmilitary major occupational groups, as defined by the Standard Occupational Classification (SOC) system of the US Bureau of Labor Statistics (BLS).[11] These data were then used for this present analysis to estimate the corresponding prevalence by comparison to the most recent BLS state occupational employment figures from May 2019.[12] These estimates were then compared to occupational data from O*NET. The O*NET database contains "hundreds of standardized and occupation-specific descriptors on almost 1000 occupations covering the entire US economy."[13] Data is continuously collected through worker surveys, and each descriptor is assessed with a question whose response is converted from an ordinal to a ratio scale. For example, the assessment of the descriptor "Disease Exposure" uses the question, "How often does this job require exposure to disease/infections?," with possible answers ranging from "never" to "every day."[14] These responses are converted to a scale between 0 and 100 for each individual occupation. Data from the category of Work Context, which encompasses the data descriptors "Interpersonal Relationships," "Physical Work Conditions," and "Structural Job Characteristics" were retrieved. Altogether, these categories contain 57 individual "physical and social factors that influence the nature of work."[15] Because data from each factor is provided for over 900 individual jobs, the arithmetic average was calculated for the jobs in each of the 22 major occupational groups to obtain the factor mean by group. For example, each factor for the individual 32 occupations under the "Personal Care and Service" major occupational group was averaged together to obtain a group factor. This was spread over the 57 individual factors to derive 1254 individual data points. Weighted averages by employment numbers were not used due to differences in the reporting of SOC classifications between BLS and O*NET datasets. Ethical approval was not required for this research because all data is assessed from publicly available sources.

2.2 | Statistical modeling

The 57 individual factors were examined, and variables most likely to influence rates of COVID-19 infection were selected based on biological plausibility. A bivariate correlation matrix was used on all factors to identify the most likely predictors to be included in regression analysis. Outliers were assessed with Cook's distance, and values greater than three times the mean distance were considered for removal. Multiple linear regression analysis was performed to observe the impact of remaining covariates on the prevalence of COVID-19 cases by occupational group, with correlation and determination coefficients reported. Standardized (β) and unstandardized (B) regression coefficients are provided with 95% confidence intervals for the latter. Statistical significance was set at $\alpha = 0.05$. All statistical testing was conducted using IBM SPSS Statistics Version 24 for Windows (SPSS Inc).

2.3 | Assessment of high-risk occupations

The resulting regression equation was applied to O*NET data by individual occupation to predict specific occupations with workers at highest risk of contracting COVID-19. Both healthcare (SOC codes beginning with 29 or 31) and nonhealthcare occupations (all other codes) were assessed. Because the absolute number of cases will always increase across all occupations, we provided predicted prevalence ratios (PR) as a measure of relative risk amongst different occupations. These ratios, along with confidence intervals for predicted values, were estimated using the formula:

$$PPR_i = \frac{PP_i}{\frac{PC - PC_i}{E - E_i}}$$

where, for any occupation i, PPR_i is the predicted PR, PP_i is the predicted prevalence, PC_i is the predicted total number of COVID-19 cases in that occupation in the United States, and E_i is the total number of workers employed in that occupation in the United States. *PC* is the predicted total number of COVID-19 cases across all occupations, and *E* is the total number of workers employed in the United States. National employment statistics from the BLS with employment figures by individual occupation for the entire United States were used for these estimations.[16] Occupations were included only if there is corresponding employment data.

3 | RESULTS

3.1 | Case counts and prevalence by occupational group

Based on statistics from the Washington State Department of Health, there were 10,850 cases of COVID-19 in Washington State tabulated by profession (Table 1). Using employment figures from the BLS, the estimated prevalence of cases ranged from 63.8 workers in the computer and mathematical occupations to 3330.3 workers in the farming, fishing, and forestry occupations per 100,000 workers employed.

3.2 | Identification of predictors of COVID-19 infection by major occupational group

Six possible O*NET predictors which might contribute to differing risks of COVID-19 infection amongst occupations were identified (Table 2) and listed with their corresponding survey questions. Mean responses by occupational group for each of these questions, translated into a ratio scale per O*NET methodology, are presented in (Table 3).

3.3 | Multiple regression analysis

A correlation matrix (Supporting Information File) demonstrated that only the O*NET predictors of disease exposure (Pearson's $r = 0.66$; $p = 0.001$) and physical proximity ($r = 0.64$; $p = 0.002$) were associated with case prevalence by occupation. The occupational group "Farming, Fishing, and Forestry" was excluded from subsequent analysis due to its extreme Cook's distance of 1.4, far exceeding three times the mean distance of 0.07. Multiple linear regression analysis showed that altogether, disease exposure and physical proximity predicted 47.5% of prevalence variance ($p = 0.003$). However, these covariates are highly

TABLE 1 Count and prevalence of COVID-19 cases by major occupational group

Major occupational group	Case count	Number employed in Washington	Estimated cases/employed × 100,000
Architecture and engineering	97	77,020	125.9
Arts, design, entertainment, sports, and media	93	49,860	186.5
Building and grounds cleaning and maintenance	579	90,590	639.1
Business and financial operations	203	225,940	89.8
Community and social service	178	52,280	340.5
Computer and mathematical	111	173,940	63.8
Construction and extraction	606	169,600	357.3
Education, training, and library	241	189,670	127.1
Farming, fishing, and forestry	741	22,250	3330.3
Food preparation and serving related	517	299,950	172.4
Healthcare practitioners and technical	1208	171,440	704.6
Healthcare support	989	144,170	686
Installation, maintenance, and repair	240	133,320	180
Legal	49	22,500	217.8
Life, physical, and social science	54	39,850	135.5
Management	667	162,850	409.6
Office and administrative support	695	392,860	176.9
Personal care and service	579	74,900	773
Production	964	178,980	538.6
Protective service	231	66,690	346.4
Sales and related	712	316,510	225
Transportation and material moving	1096	263,330	416.2

Abbreviation: COVID-19, coronavirus disease 2019.

TABLE 2 Possible predictors of COVID-19 risk with corresponding O*NET survey questions

O*NET predictor	O*NET survey question
Contact with others	How much does this job require the worker to be in contact with others (face-to-face, by telephone, or otherwise) in order to perform it?
Cramped work space, awkward positions	How often does this job require working in cramped work spaces that requires getting into awkward positions?
Duration of typical work week	Number of hours typically worked in one week.
Exposed to disease or infections	How often does this job require exposure to disease/infections?
Face-to-face discussions	How often do you have to have face-to-face discussions with individuals or teams in this job?
Physical proximity	To what extent does this job require the worker to perform job tasks in close physical proximity to other people?

Abbreviation: COVID-19, coronavirus disease 2019.

collinear ($r = 0.78$; $p < 0.0001$) and alone are not independent contributors to the regression model ($\beta = 0.4$; $p = 0.16$ for disease exposure, $\beta = 0.33$; $p = 0.25$ for proximity; Table 4).

3.4 | Prediction of occupations with highest COVID-19 risk

The resulting linear regression model was applied to every individual SOC on O*NET for which there exists corresponding employment data with the BLS to predict the specific professions at highest risk of COVID-19. The 15 occupations which overall have the highest predicted risk are all healthcare professions, with four of the top five in the dental health field (Table 5). The highest risk nonhealthcare occupations are also provided (Table 6).

4 | DISCUSSION

There is ample precedent for the use of O*NET datasets to estimate occupational risk from various exposures in occupational health research, particularly in the absence of field data on the individual level.[10,17] Other studies have used this approach to explore predictors of outcomes as varied as carpel tunnel syndrome,[9] hearing loss,[18] and pregnancy-associated stress.[10] More recently in the case of COVID-19, this method was applied to estimate the total number of workers across the United States at risk of exposure to disease or infection on a weekly and monthly basis,[19] and to identify differential occupational risk according to race and ethnicity.[20] An analogous study in Italy used the Italian equivalent of O*NET to determine sectors most at risk of COVID-19 exposure by identifying those industries that require physical proximity in order to operate.[21] In the present retrospective analysis, O*NET data was correlated for the first time with real case counts to provide a regression model of exposure risk, and it was found that the predictors of disease exposure and physical proximity predicted 47.5% of the variance of case prevalence by occupation. Furthermore, this model was used recursively on individual SOC classifications to estimate the specific occupations at highest risk.

Although this study is based upon case numbers from only a single state, extrapolation to the whole of the United States yields predicted case counts that are in line with actual estimates. COVID-19 cases with employment data are provided for Washington State up to June 16th 2020, at which time there were around 1.68 million cases in the United States.[22] Applying the regression model to the entire working population of 147 million in the US results in a total predicted case count of 484,000 workers, a very close figure considering that counts from Washington contained occupational data from only 41% of cases, and the employment to population ratio is generally 50%–60%.[23] Nevertheless, it is important to note that predicted case numbers are not so relevant as relative figures. Not only are case counts underestimated due to incomplete data, but, cumulative total case counts will always increase over time. Therefore, occupational risk is better captured through predicted PR rather than absolute predicted prevalence.

It is not surprising that HCWs, especially those at the frontline in the battle against COVID-19, are at the highest risk.[6] After all, both the general risk of disease exposure and physical proximity are higher in this group than in any other, and any model which uses these factors as risk predictors will be dominated by HCWs. Even within HCWs, however, there are some workers which are predicted to be particularly at risk. Of note, fully half of the predicted riskiest occupations are in the dental field, which faces unique challenges during this pandemic. Although data on COVID-19 cases are not available, it is clear that "the unique nature of dental interventions, which include aerosol generation, handling of sharps, and proximity of the provider to the patient's oropharyngeal region"[24] exposes dentists and oral health professionals to infection.[25] "The risk is considered to be higher in dental practices than in other healthcare settings,"[26] and as neither social distancing nor remote work is possible, dental professionals must take special precautions to avoid infection,[27] and some have elected to close their offices altogether.[28] Nonhealthcare occupations at the highest risk of COVID-19 infection are dominated by workers who are either in close direct contact with others, such as flight attendants, teachers, barbers, jailers, and transportation security screeners, or may be directly exposed to SARS-CoV-2 (ambulance drivers, morticians, embalmers). Other than

TABLE 3 Mean values of O*NET predictors by occupational group, scaled 0–100

Major occupational group	Contact with others	Cramped work spaces	Duration of work week	Exposure to disease	Face-to-face discussions	Physical proximity	Number of occupations
Architecture and engineering	78.1	23.3	78.3	5.8	92.8	50.6	70
Arts, design, entertainment, sports, and media	84.2	16.2	58.1	6.9	86.3	58.7	43
Building and grounds cleaning and maintenance	75.5	37.4	58	25.5	85.3	53	8
Business and financial operations	87.3	11.2	73.9	6.5	89.3	49.7	50
Community and social service	94.1	11.9	59.9	44.4	95.5	62.1	14
Computer and mathematical	76.7	10.5	75.4	3.8	87.8	45.9	32
Construction and extraction	80.9	57.7	64.5	12.6	89.9	69.1	60
Education, training, and library	86.4	8.7	68.2	19.5	90	57.6	61
Farming, fishing, and forestry	71.4	28.3	74.6	15.5	82.4	44.5	17
Food preparation and serving related	85.8	22.8	27.9	15.4	83.7	71.9	17
Healthcare practitioners and technical	92.2	26.5	61.1	79.6	95.4	84.6	86
Healthcare support	92	29.7	39.9	77.7	90.1	84.7	18
Installation, maintenance, and repair	81.1	58.7	70.4	12.4	88.2	62.4	54
Legal	81.4	6.4	59.6	13.3	93.1	48.9	8
Life, physical, and social science	76.8	15.4	75	14.8	91.6	48.8	60
Management	89.2	13.3	83.8	10.6	94.2	49.2	56
Office and administrative support	91.3	12.7	51.8	14	87.4	57.5	63
Personal care and service	90.1	17.3	43.6	29.7	87.3	77.1	32
Production	71.8	31.3	65.1	7.3	84.6	56.7	110
Protective service	91.2	33.6	63.5	45.8	89.9	70.4	29
Sales and related	93.3	10.3	62.5	6.9	89.4	59.1	24
Transportation and material moving	84.2	43.2	69.3	16.3	87.1	61.1	53

Note: Higher is more frequent.

TABLE 4 Results of multiple linear regression analysis of disease exposure and physical proximity on case prevalence

	β	*B*	95% CI lower	95% CI upper	*F* value	R^2	*p*
Model					8.14	0.475	**0.003**
Disease exposure	0.4	4.03	−1.79	9.85			0.16
Physical proximity	0.33	6.32	−4.75	17.39			0.25

Note: Bold value provide statistically significant.
Abbreviation: CI, confidence interval.

teachers, none of these workers have the option of working remotely, and specific on-the-job interventions are required to protect these workers.

The differential risk of occupational COVID-19 also leads to differential economic outcomes for those especially at risk. New cases are associated with continued negative effects on the labor market,[29] and given the intimate interconnection between physical health and economic health,[30] the contributions of the latter to both individual and societal well-being must not be understated. Indeed, much research, particularly in the labor economics literature, have employed a similar approach using O*NET or similar data to explore the relationship between occupational characteristics and economic outcomes to create models of economic disparities by occupation or industry. One early study used differential telework ability and essential worker distribution to identify negative labor shocks by occupation,[31] while another examined the same outcome using physical proximity predictors from O*NET.[32] Other studies have used O*NET data to create indices reflecting the ease of remote work, and concluded that the economic burden of COVID-19 falls disproportionately on low income workers,[33,34] women, and workers with low educational attainment.[35] These economic outcomes represent variable social determinants of health that are crucial in understanding the differential impact of COVID-19 on individuals and populations[36] and may lend support to social insurance as a means to reduce hardship in particularly vulnerable workers.[37]

TABLE 5 Estimated individual occupations at highest risk

SOC code	Occupation	Predicted prevalence ratio	95% CI
29-2021.00	Dental hygienists	2.71	1.28–4.13
29-1022.00	Oral and maxillofacial surgeons	2.67	1.26–4.07
31-9091.00	Dental assistants	2.64	1.24–4.05
29-1021.00	Dentists, general	2.62	1.23–4.02
31-1015.00	Orderlies	2.61	1.22–4
29-1124.00	Radiation therapists	2.6	1.22–3.98
29-1064.00	Obstetricians and gynecologists	2.57	1.19–3.94
29-1126.00	Respiratory therapists	2.54	1.16–3.93
29-1062.00	Family and general practitioners	2.53	1.13–3.93
29-1141.00	Registered nurses	2.61	1.16–4.14
29-1024.00	Prosthodontists	2.51	1.15–3.88
29-2099.06	Radiologic technicians	2.52	1.16–3.88
29-1161.00	Nurse midwives	2.51	1.15–3.86
29-2041.00	Emergency medical technicians and paramedics	2.51	1.15–3.88
29-1122.00	Occupational therapists	2.51	1.15–3.87

Abbreviation: CI, confidence interval.

There are numerous limitations to the present research, particularly on the dataset level. Potential limitations of O*NET data have previously been discussed, particularly misclassification, undercounting, failure to account for exposure variation within occupations, and bias due to the subjective nature of the questionnaires.[19] From a COVID-19 specific standpoint, O*NET data cannot be expected to reflect more recent changes in the working environment as a consequence of the pandemic. These changes can be intentional, in the form of measures aimed specifically to reduce exposure risk, or unintentional, due to social or economic fallout. For example, the predictor of physical proximity does not adequately capture the practice of social distancing or the push to work from home in many industries. Meanwhile, it is possible that the risk to transportation workers might be less than predicted due to reduced overall travel demand.

The use of only two O*NET variables, physical proximity and disease exposure, does not adequately represent the myriad of other factors that might affect occupational risk. For example, recent research has suggested that race and ethnicity may influence differential risk amongst occupations, but individual O*NET predictors are not further delineated by these factors. Only by calculating the percentage of essential workers by race employed in occupations at high risk could the influence of these factors be detected.[20] This may explain the highly anomalous case count in the farming, fishing, and forestry major occupational group. Although comprising only 3% of employed workers in Washington, this group represents 11% of all COVID-19 cases, a greater overrepresentation than even healthcare providers, and was excluded from this regression analysis. On closer inspection, it can be noted that this group accounts for a staggering 14% of the cases amongst Hispanics, and only less than 1%, 2%, and 2% amongst non-Hispanic Whites, Asians, and Blacks, respectively, yet this figure is tempered by noting that 14% of the Hispanic population in Washington is employed in that occupation. Differential occupational placement by ethnicity clearly influences case numbers, but O*NET predictors fail to take this into account.

In addition, there are significant limitations with the Washington State data. As noted previously, only 41% of COVID-19 cases in

TABLE 6 Estimated individual nonhealthcare occupations at highest risk

SOC code	Occupation	Predicted prevalence ratio	95% CI
53-2031.00	Flight attendants	2.34	1.02–3.68
33-2011.01	Municipal firefighters	2.21	0.94–3.5
53-3011.00	Ambulance drivers and attendants, except emergency medical technicians	2.17	0.90–3.43
39-5011.00	Barbers	2.1	0.76–3.44
25-2012.00	Kindergarten teachers, except special education	2.04	0.81–3.28
33-3012.00	Correctional officers and jailers	2	0.76–3.24
33-1011.00	First-line supervisors of correctional officers	1.96	0.56–3.37
39-4031.00	Morticians, undertakers, and funeral directors	1.91	0.57–3.24
33-1021.01	Municipal fire fighting and prevention supervisors	1.88	0.65–3.13
33-9093.00	Transportation security screeners	1.88	0.66–3.11
25-2051.00	Special education teachers, preschool	1.86	0.62–3.11
47-4071.00	Septic tank servicers and sewer pipe cleaners	1.83	0.63–3.03
39-4011.00	Embalmers	1.8	0.32–3.29
25-2053.00	Special education teachers, middle school	1.79	0.6–2.97
21-1093.00	Social and human service assistants	1.79	0.6–2.98

Abbreviation: CI, confidence interval.

Washington contained occupational information, although this figure was 57% for those between the ages of 18–64. However, “in 2019, an estimated 73% of the population [in this age range] were employed.”[7] The reason for this discrepancy is not known, and raises the possibility of group differences, not only between all cases with employment data and all cases without, but also between the former and the cases who should have been recently employed but did not provide data. Furthermore, because all state data is provided as static aggregate sums reflecting cases from inception until June 2020 without further delineation into discrete time periods, it is not possible to track changes in case trends that might reflect changing practices in the workplace in response to the pandemic. However, any further temporal analysis must also take into account overall community transmission levels.

Due to these and other limitations, more extensive case data tabulated by occupation are needed to fully understand the impact of COVID-19 on the working population. Industry specific recommendations to guide mitigation efforts are currently available from federal[38] and state[39] agencies, including Washington.[40] These address settings where workers are at particularly high risk, including healthcare facilities,[41] dental offices,[42] restaurants,[43] and beauty salons.[44] However, any recommendations or policy changes considered will benefit from more accurate occupational data. Although the case count of HCWs is actively updated,[45] data for other occupations are lacking, and even HCW data is not delineated by individual occupation. As noted by the CDC, “without good surveillance data on the jobs of all workers with COVID-19, it's hard to tell what groups are at higher risk because of their jobs.”[46] Collecting data on occupation and workplace, if employed, is now recommended as part of risk assessment during COVID-19 case interviews.[47] These initiatives should yield improved data on the occupational risk of COVID-19 and should guide the implementation of occupation-specific interventions aimed at reducing this risk. The health and safety of millions of workers are at stake.

5 | CONCLUSION

Occupational risk of COVID-19 infection is not uniform across occupational groups. Physical proximity and general disease exposure are risk factors, but do not fully capture the extent of differential risk across occupations. Recent measures such as social distancing and remote working may not be reflected in these predictors, and not all measures are equally applicable to every occupation. HCWs, particularly those in the front lines and in the dental professions, remain at particular risk. More comprehensive data is needed on the individual occupation level, preferably across the entire United States, to fully assess worker risk and direct protective measures tailored to individual occupations.

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CONFLICT OF INTERESTS

The author declares that there are no conflict of interests.

DISCLOSURE BY AJIM EDITOR OF RECORD

John Meyer declares that he has no conflict of interest in the review and publication decision regarding this article.

AUTHOR CONTRIBUTIONS

Michael Zhang has sole responsibility for study conceptualization, design, data collection and interpretation, and manuscript writing, and is solely accountable for all aspects of this work.

DATA AVAILABILITY STATEMENT

Public data used in this study are available from O*NET[15] and the Washington Department of Health.[7]

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SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section.

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