INFANT MORTALITY RESEARCH PARTNERSHIP

Reducing Infant Mortality in Ohio: Individuals, Communities, Systems, and Interventions

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Ohio Colleges of Medicine Government Resource Center

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EXECUTIVE SUMMARY

The Infant Mortality Research Partnership (IMRP) was a collaboration between state agencies, researchers, and subject matter experts to bring rigorous and innovative methodological approaches to lowering infant mortality in Ohio. The IMRP, leveraging a diverse array of data and methods, sought to answer three overarching questions: **1)** *Where*, within Ohio, should interventions be targeted to reduce infant mortality? **2)** *To whom* should those interventions be targeted (i.e., which women are at highest risk)? and **3)** *How* should those interventions be implemented, and what will be the likely future impact of these interventions?

Major findings and contributions of the IMRP include the following:

1. **Race and ethnicity have a complex association with infant mortality and preterm birth**. Non-Hispanic Black (NHB) race/ethnicity was associated with increased odds of infant mortality in all individual models. Living in a high concentration NHB neighborhood was also associated with increased odds of infant mortality and pre-term birth. However, when factors such as housing, provider density, and food deserts were accounted for, the racial/ethnic composition of neighborhoods was no longer an important risk factor for infant mortality. This suggests that the simple association between race/ethnicity and infant mortality *is not as important as the socioeconomic and structural factors that increase neighborhood risk*. These can be appropriate targets for intervention.

2. **Medical complications and prior obstetrical history are major risk factors for infant mortality and preterm birth.** Increasing access to quality prenatal care and primary care in Ohio may reduce infant mortality and preterm birth.

3. **Severe mental illness in the prenatal period and inadequate follow-up care for mental illness are associated with infant mortality.** Interventions could be focused on improving the integration of mental health services with prenatal care.

4. **Increasing the appropriate use of progesterone therapy,** and funding this intervention using a *capture and reinvest* strategy, will likely lead to reduced infant mortality rate at minimal additional cost.

5. **Increasing access to long-acting reversible contraceptives** would decrease the number of unintended births, disproportionately decreasing higher risk pregnancies such as those following short inter-pregnancy intervals, and result in saving $15 million in direct medical costs.

6. **Living in an area with a high homicide rate increases the risk of infant mortality as well as preterm birth.** Interventions to make neighborhoods safer could have an impact on the health of women and infants in Ohio.

7. **Infant mortality in rural areas may be associated with different risk factors than urban areas**, but further research is required to understand this difference.

8. **A disproportionately large portion of infant deaths in Ohio occurs at pre-viable gestational ages compared to other states**. A larger proportion of pre-viable live births occurs to NHB women, and may contribute to Ohio's racial disparity in infant mortality. More investigation is needed to determine how this should be addressed.

This work represents a major first step in better understanding and addressing this public health issue for Ohio women and infants.

SECTION 1: INTRODUCTION AND BACKGROUND

1.0 Background and Rationale

The infant mortality rate (IMR), defined as the number of deaths in the first year of life per 1,000 live births, reflects not only maternal and infant health but also the overall health of a community, state, or nation.(1) In the United States, the IMR has progressively declined in recent years to reach 5.87/1,000 in 2015, a rate below the Healthy People 2020 goal.(2) However, the IMR for non-Hispanic Black (NHB) infants in many U.S. states and cities is more than twice as high as for non-Hispanic White (NHW) infants.

In 2013, Ohio had one of the higher reported IMRs in the United States.(3) A variety of strategies, including national, statewide, and community-based initiatives, have been undertaken to reduce both the overall IMR in Ohio and narrow its racial disparity. In 2015, Ohio's rate had improved to 7.2/1,000; however, the NHB IMR remained almost three times the rate for NHW infants.(4) Previous work has suggested that up to one third of this disparity may reflect Ohio's reporting of pre-viable live births as liveborn, a disproportionate number of which are NHB infants.(5)

To reduce this disparity, The Ohio Department of Health (ODH) joined the national Institute for Equity in Birth Outcomes initiative and designated the nine counties and communities in which the majority of Ohio's NHB babies are born as Ohio Equity Institute (OEI) communities. Building on the Ohio Department of Health Infant Mortality Reduction plan and the Ohio Commission on Infant Mortality report, legislators enacted S.B. 332. Also known as the Infant Mortality Reduction Bill, it contains provisions that address factors known to affect infant mortality. For example, it supports strategies to reduce premature births by increasing availability and use of progesterone therapy, and to reduce unintended pregnancies via long-acting reversible contraceptives (LARC). The State Health Improvement Plan for 2017-2019 includes a strong focus on maternal and infant health to achieve health equity and reduce infant mortality. To examine the specific risk factors for different populations as well as individual risks, a more coordinated effort, grounded in Ohio-specific data, was needed.

Infant mortality is a complex problem with varied contributing factors that are themselves often interacting, and as such effective solutions require a multi-pronged, multi-sector approach.(6) Poor birth outcomes such as preterm birth (PTB, defined as birth prior to 37 weeks gestation), very preterm birth (<28 weeks), low birth weight (LBW, defined as weight <2500 grams), very low birth weight (<1500 grams) and infant mortality have long been understood as the result of medical risk factors (high blood pressure, diabetes, short cervix, etc.), and factors related to social and behavioral health (e.g., socioeconomic status, racism, neighborhood characteristics, access to prenatal care, smoking, alcohol or drug abuse). Researchers and policymakers alike increasingly recognize the role of structural and institutional factors (i.e., social determinants of health) that directly and indirectly impact maternal and child health, as well as their relationship to medical, psychosocial, and demographic risk factors.(7, 8) By identifying these complex, contributing factors of infant mortality and the interactions among them, a more effective set of interventions responsive to the various populations and geographic regions across the state of Ohio, can be developed and implemented.(9, 10)

The need for a statewide research collaboration to address this public health issue was identified by the Ohio Legislature, the Governor's Office of Health Transformation (OHT), and the Ohio Departments of Medicaid (ODM), Health (ODH), and Higher Education (ODHE). The Infant Mortality Research Partnership (IMRP) was launched in this spirit. The IMRP project design incorporated multiple methodologies to span multiple domains and levels. The design was intended to explicitly model nuance in infant mortality risk factors (i.e. move beyond poverty as the primary risk factor), as well as capture a cohesive and more comprehensive portrait of the complexity of infant mortality.

The Ohio Colleges of Medicine Government Resource Center (GRC) was charged with administering the IMRP. GRC constructed the linked research files, provided project infrastructure, and oversaw all aspects of the project. Following a competitive application process, the state sponsors selected four research teams comprising scholars with extensive clinical and methodological expertise from across the state of Ohio to address the distinct research questions and IMRP project tasks. These research teams represented six Ohio Universities and spanned a wide range of disciplines including engineering, geography, medicine, public health, and social work. In addition, subject matter and methodological experts were selected to provide consultation to each respective research team, providing guidance and input throughout the duration of the project.

1.1 Data Used for the IMRP

This initiative employed an innovative approach to identify the causes of infant mortality and to determine the best mix of interventions to reduce the IMR. Driving this multi-method, interdisciplinary approach was the construction of a multidimensional dataset. Thanks to a multi-agency effort, facilitated by data preparation, linkage and management by GRC, infant mortality researchers had access to comprehensive, linked datasets that included physical and mental health variables, indicators of numerous social determinants of health, and data on the utilization of some community and government programs. (See Table 1 for the full list of available datasets.) This application of big data to the pervasive, complex problem of infant mortality enabled researchers to develop more accurate models of the factors impacting risk, and the interventions that can improve maternal and child health outcomes across the state of Ohio.

Table 1: Datasets Used by the IMRP Research Teams

Dataset	Source/URL	Teams that used dataset
Medicaid Claims	Ohio Department of Medicaid	GEO, SD, PM
Women of Reproductive Age (WRA)	grc.osu.edu/Projects/MEDTAPP/WomenOfReproductiveAge	GEO, PM
Ohio Vital Statistics -Births	odh.ohio.gov/healthstats/vitalstats/vitalstatsmainpage.aspx	GEO, PM
Ohio Vital Statistics -Deaths	odh.ohio.gov/healthstats/vitalstats/vitalstatsmainpage.aspx	GEO, PM
American Community Survey	census.gov/programs-surveys/acs/news/data-releases.html	GEO
Ohio Business Listings	infousa.com/product/business-lists/	GEO
USDA Food Deserts	ers.usda.gov/data-products/food-access-research-atlas/download-the-data/	GEO
Foreclosure data	huduser.gov/portal/datasets/nsp_foreclosure_data.html	GEO
Homicide deaths 2007-2014	odh.ohio.gov/healthstats/vitalstats/vitalstatsmainpage.aspx	GEO

Abbreviations: GEO: spatiotemporal; SD: systems dynamics; PM: individual predictive model; USDA: United States Department of Agriculture.

1.2 Overview of the Methodology

The IMRP comprised three distinct multidisciplinary research teams, each conducting data analyses toward answering one of the partnership's key questions. A fourth team provided project oversight, subject and methodological expertise, and worked with the other research teams and GRC to develop this final report and accompanying *Methodology Report*. This fourth team also performed individual predictive modeling. A description of each team's roles, methodologies, and products are below; please see the last page for a full list of IMRP members and their respective institutional affiliations.[1]

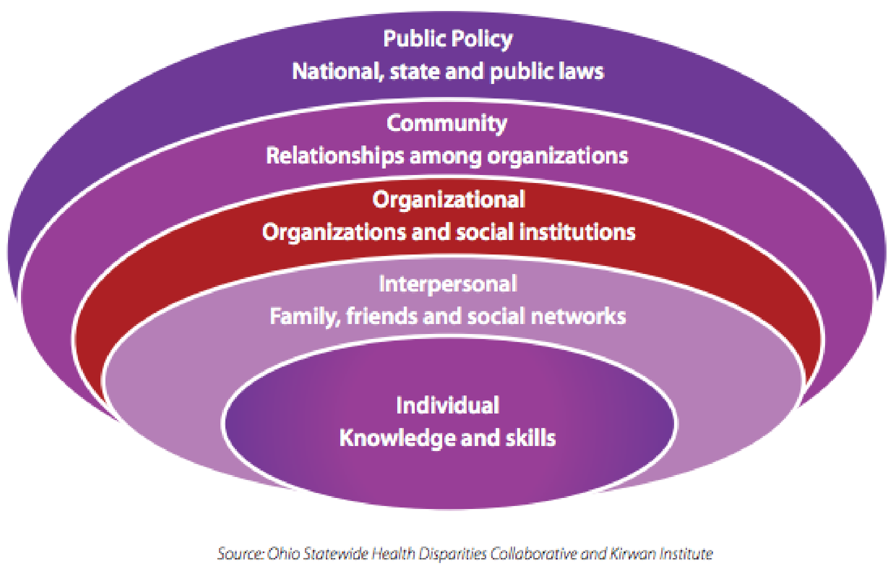
GRC oversaw all aspects of the IMRP initiative, coordinated project communications and activities, and developed and implemented methodologies to link the majority of the project datasets together. GRC provided ongoing support to research teams as they began analyzing these project data and conducted intensive reviews of their interim and final project outputs. Most teams conducted their analyses and developed their interactive outputs within the technological infrastructure GRC developed and supported for the project.

IMRP researchers aimed to improve understanding of the factors contributing to infant mortality and preterm birth in Ohio, building a foundation from which to design and implement

[1] The population predictive modeling was not completed in time to be included in this report.

targeted interventions. Teams took into account factors recognized in research literature as consequential to IM and PTB. These factors span multiple levels, as illustrated by the socio-ecological framework (see Figure 1).(11) The individual predictive models and multilevel spatiotemporal models addressed individual and organizational risk factors. The spatiotemporal models included community risk factors. Finally, the systems dynamics models addressed organizational and public policy levels to determine the impact of interventions. By using these models together, the project aimed to include the most relevant factors at each of these levels that contribute to infant mortality.

Figure 1: The Socio-ecological Model (11)



1.2.1 Researchers' Roles and Deliverables

Each team worked independently within their own methodological area of expertise. However, cross-team collaboration was encouraged to discuss data and analysis decisions and identify complementary processes or findings that could complement the work of another team. This collaboration was facilitated through bi-monthly data review meetings and quarterly executive committee meetings. Each team was also responsible for providing a section for the *Methodology Report* encapsulating their full study design, methods, and results, as well as a summary contribution to this *Final Report*. A brief overview of the teams' goals and approaches is provided below, and more detailed summaries, including their primary results are provided in subsequent sections of this report.

1.2.1.1 Spatiotemporal Analysis of Infant Mortality and Preterm Birth in Ohio

Guided by the recognition that "place matters," this team utilized geospatial methods to identify the Ohio communities with the highest rates of infant mortality, incorporating social determinants of health, access to care, and areas of insufficient healthcare service availability. Researchers were able to identify clusters in Ohio where women had an elevated risk of experiencing poor birth outcomes, after adjusting for demographic composition. They integrated key neighborhood characteristics such as racial segregation and neighborhood crime rates, measuring risk defined by factors from the women's communities of residence as well as their own characteristics. In addition to identifying geographic areas of high risk, the team demonstrated how spatial data can be used as an aid in targeting interventions and evaluating interventions' impact: Researchers conducted a case study, cataloging existing programs that address infant outcomes in Franklin County, to explore area-level associations between those interventions and IMR reduction.

1.2.1.2 Systems Dynamics Modeling of Infant Mortality in Ohio

Following the need to take a systems approach to measuring the benefits and cost of interventions, this team used systems dynamics modeling to simulate the impact of various interventions on the reduction of infant mortality. The team utilized participatory research in group model building sessions to draw upon the expertise of various maternal and child health stakeholders including researchers, practitioners, and representatives from community agencies and organizations. Insights gleaned from these sessions informed the development of the team's conceptual framework for the development of a systems dynamics model simulating the impact of implementing a progesterone therapy intervention and increasing access to LARC.

1.2.1.3 Individual Predictive Modeling of Preterm Birth and Infant Mortality and Project Coordination

This IMRP team's primary research activity was developing predictive models that could be used at the point of care by healthcare providers, toward identifying patients at high risk of infant mortality or preterm birth. The primary goal of this work was to incorporate these models into a set of tools that could be used like the American College of Obstetricians and Gynecologists (ACOG) pregnancy risk assessment form.(12) In addition they developed a tool using predictive models to aid policymakers identify possible impacts of targeted interventions on the Medicaid population.

This IMRP team was also the coordinating team, acting as the facilitator for the other teams throughout the duration of the project. The primary responsibilities of this team were to chair the IMRP advisory committee, ensure the other teams were making adequate progress, facilitate collaboration across teams when necessary, and provide support through their extensive subject matter and methodological expertise. The coordinating team was also charged with working collaboratively with GRC and the other research teams to integrate the products of each team for this *Final Report* and the more detailed *Methodology Report*.

Each research team was responsible for developing their component of the Infant Mortality Reduction Analytics Dashboard, but the coordinating team worked with GRC to oversee those efforts and standardize the outputs. The primary purpose of the dashboard was to ensure that the highly technical output of each of the IMRP research teams was effectively translated for stakeholders, so that all project results could inform policy decisions. In order to ensure the dashboard was responsive to stakeholder needs, the coordinating team held ongoing meetings with users of the display, presenting use cases and soliciting input to improve upon its usability.

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SECTION 2: SPATIOTEMPORAL ANALYSIS OF INFANT MORTALITY AND PRETERM BIRTH IN OHIO

2.1 Introduction and Objectives

Geography plays a major role in understanding the dynamics of health. People, and the factors that lead to both good and bad health outcomes, are dispersed -- often unevenly -- across communities and regions.(1) This dispersion leads to unique spatial patterns of many health outcomes, including low birth weight (LBW) and preterm birth (PTB), infant mortality (IM), and a variety of birth defects. The availability of geographic data provides policymakers and public health officials with the capability to perform two unique types of analysis: 1) finding areas of high or low incidence worthy of further investigation, and 2) examining the spatial relationship between health outcomes on the one hand, and population and contextual factors on the other, that vary across space.(2,3)

This study used mapping and spatial analysis to identify high-risk communities in Ohio that can be targeted for intervention and resource allocation, and to provide a deeper understanding of why these communities are high risk. These efforts addressed three major objectives:

1) Examine individual-level and area-level risk factors associated with infant mortality and preterm birth in Ohio
2) Examine spatial patterns and clusters of infant mortality and preterm birth in Ohio
3) Demonstrate how spatial analytic techniques can be used for program planning and evaluation

2.2 Methods

This study used a combination of Geographic Information Systems (GIS), geovisualization and mapping, and statistical modeling to examine the spatial patterns of infant mortality and preterm birth in Ohio. In order to conduct a spatial analysis, all Ohio birth and death records were geocoded so data could be displayed on a map. Once records were geocoded, each record was assigned a census tract in the GIS and merged with a variety of area-level data (e.g., median household income or OB/GYNs per capita). Then, using multilevel models (MLMs) and spatial cluster analysis, two primary outcomes were examined: infant mortality and preterm birth. This report presents results for the Medicaid Women of Reproductive Age (WRA) cohort; the *Methodology Report* includes analyses of the full Ohio birth cohort.

Multilevel models are used when observations in a data set are nested or grouped. (4,5) When observations are nested within a group such as residents of the same census tract, they tend to be more alike than data from individuals selected at random across tracts. These within-group similarities require statistical models that account for this phenomenon. This study used multilevel models to estimate the probability of infant mortality or preterm birth event as a function of both individual- (e.g., age, education, hypertension, etc.) and area-level (e.g., racial concentration, residential stability, poor housing, etc.) factors.

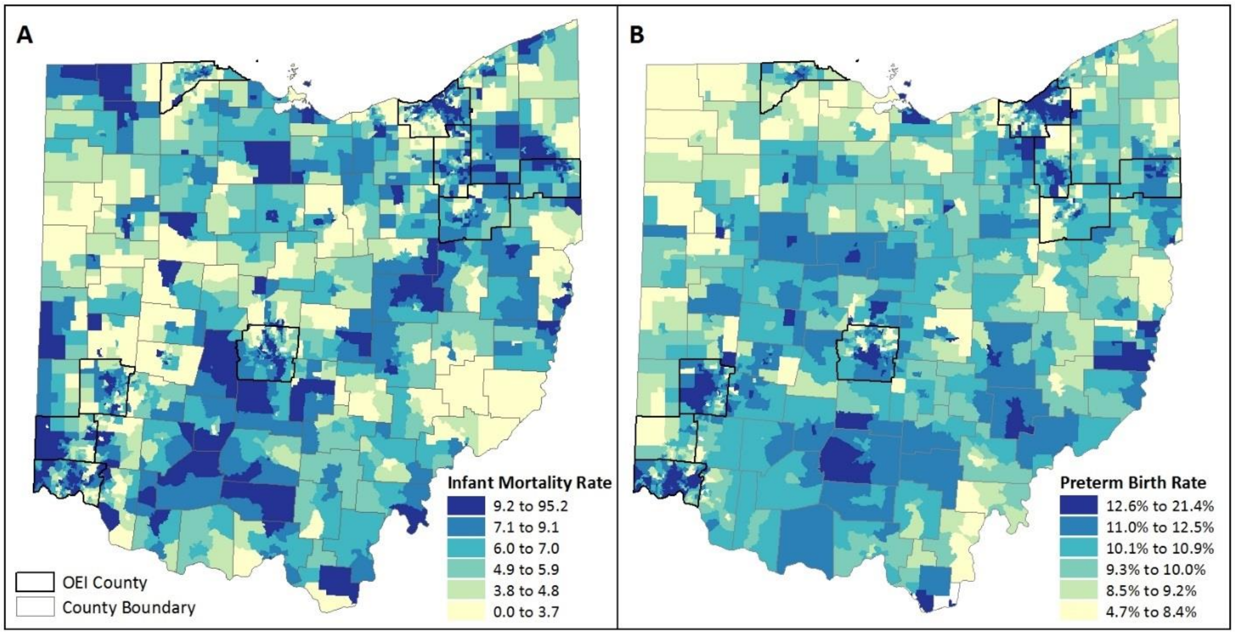
The spatial scan statistic is one of the main epidemiological tools to detect the presence and locations of geographic clusters of health events.(6) This method tests whether there is an elevated risk (e.g., more cases than would be expected) within a specific geographic area as compared to outside that area. In this case, using the observed number of infant deaths or preterm birth cases, an expected number was calculated based on: 1) population density or 2) population density by maternal age, race/ethnicity and education. Considering population density assured that the reported clusters were not merely due to a large number of births in an area. Additional adjustment for maternal characteristics also ensured that clusters were not simply reflecting uneven distributions of populations with known risk factors, such as a large concentration of NHB mothers. Results of the scan statistic were mapped using the GIS. Relative risk is reported for all clusters with a p-value < 0.05.

This work includes a case study to demonstrate how spatially referenced data can be used to support program evaluation or planning activities. A formal program evaluation, that establishes causal links between programs and changes in birth outcomes, was not conducted. Rather, the case study shows, for limited geographic areas, how to: create a spatial database of current activities in a defined geographic region; integrate this database with other contextual data in the GIS; and apply spatial overlay techniques to examine the concurrent location of programs and services with populations in need.

2.3 Key Findings

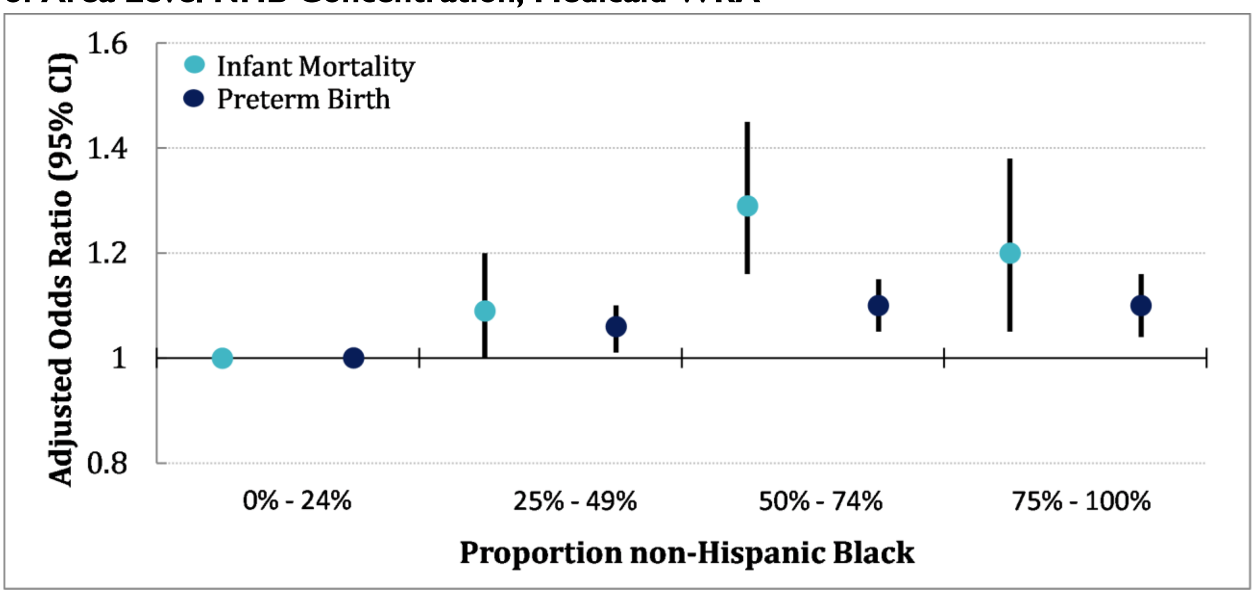
Figure 2 shows rate maps for infant mortality (Panel A) and preterm birth (Panel B) for the Medicaid WRA cohort. The Medicaid WRA cohort includes a subset of all Ohio births, and looks somewhat different than the full Ohio birth cohort. There are a higher proportion of low-income and NHB mothers in the Medicaid WRA cohort. The legend is standardized across maps for ease in comparison and the Ohio Equity Institute (OEI) counties (7) are outlined in black.

Figure 2: **Spatially Smoothed Rate Maps of: A) Infant Mortality (Per 1,000 Births) and B) Preterm Birth, Medicaid WRA Cohort 2008-2015**



The patterns look similar between the two maps; all major cities have concentrations of high infant mortality and preterm birth, and there is a distinct dark band through Appalachia.

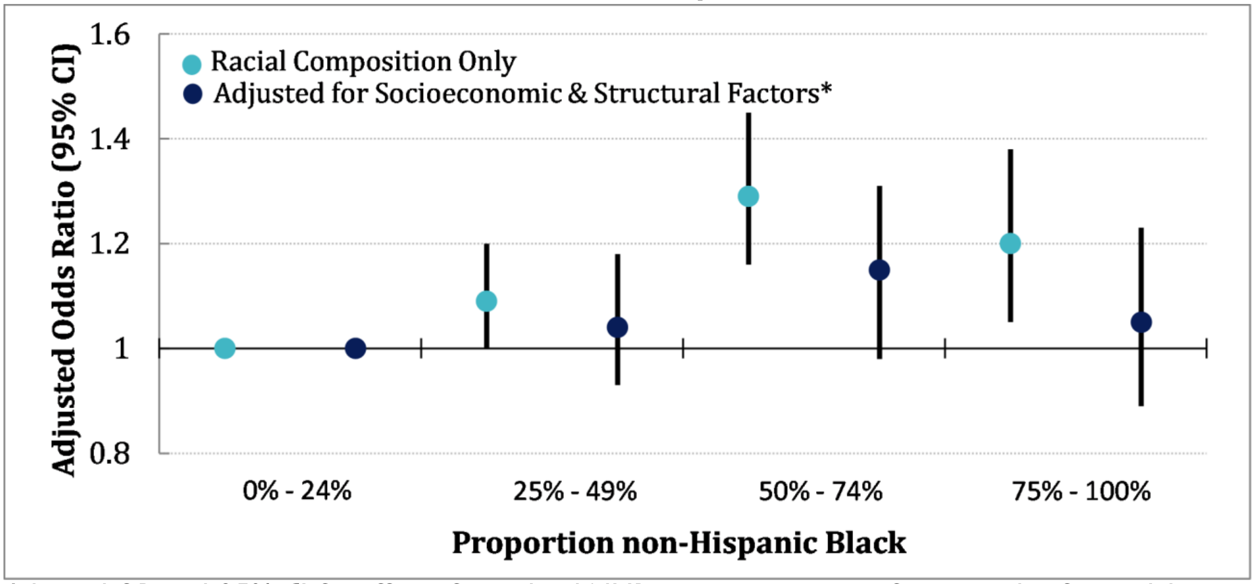
Figure 3: **Adjusted Odds Ratio (OR) and 95% Confidence Interval (CI) for the Effect of Area Level NHB Concentration, Medicaid WRA**



There is an Elevated Risk for Infant Death and Preterm Birth in Neighborhoods with a High Concentration Of NHB Residents

The teal dots in Figure 3 show the increase in odds of infant mortality from living in increasing NHB concentrated neighborhoods. Compared to neighborhoods with 0% to 24% NHB residents, the odds of an infant death in neighborhoods with 50% to 74% NHB residents were approximately 30% greater. The dark blue dots show this same relationship for preterm birth. The odds were about 10% higher for preterm birth in neighborhoods with 50% to 74% NHB residents neighborhoods compared to 0% to 24% NHB residents.

Figure 4: Infant Mortality Model: The Impact of Adjusting for Socioeconomic & Structural Factors on the Effect of Racial Composition

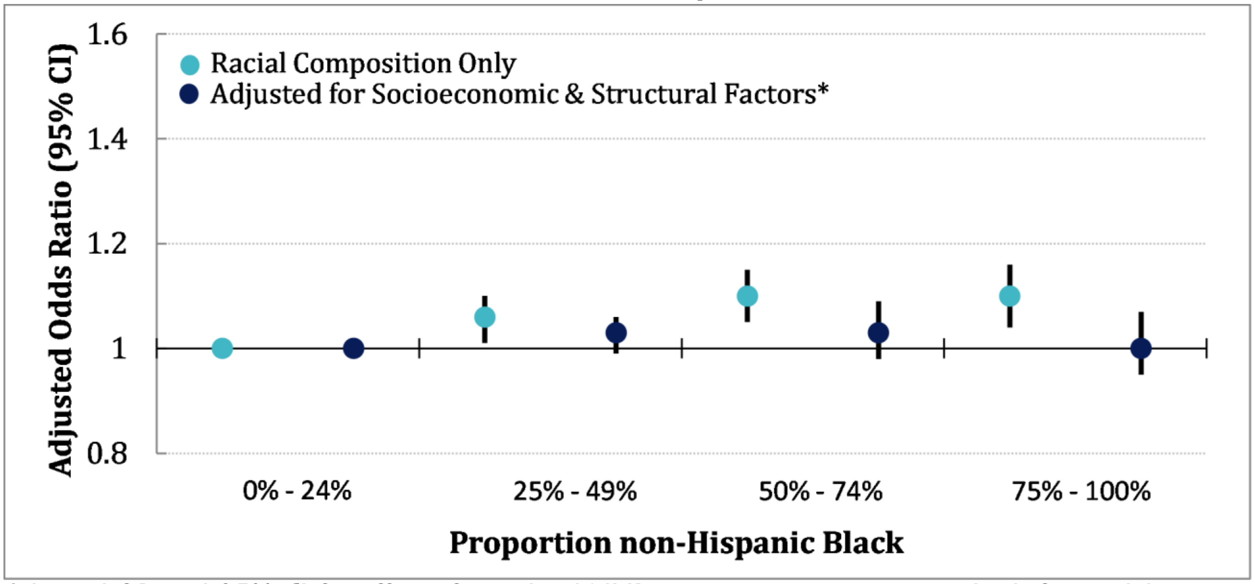


Adjusted OR and 95% CI for effect of area-level NHB concentration on infant mortality for models including racial composition only and racial composition and socioeconomic/structural variables, Medicaid WRA cohort 2008-2015

Area-Level Socioeconomic and Structural Variables Help Explain Much of the Effect of Living in a High Concentration* NHB *Neighborhood on Infant Mortality

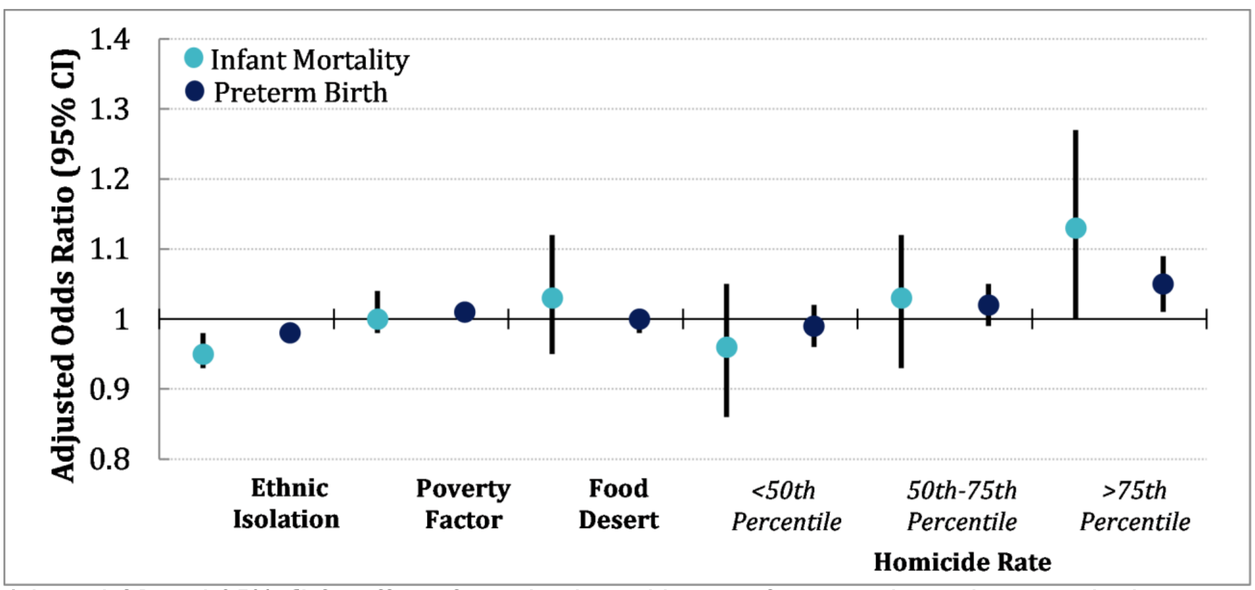
Figure 4 shows the results of two different models for infant mortality. The teal dots show the effect of living in a high concentration NHB neighborhood when no other neighborhood factors are considered. The dark blue dots indicate the effect of living in a high concentration NHB neighborhood when additional socioeconomic/structural factors are considered (e.g., residential stability, food deserts, and health provider density). For all neighborhoods, the odds decrease when the model adjusts for socioeconomic/structural factors; in the 75% to 100% NHB neighborhoods adjustment for these factors yields a decrease from a 20% greater odds of infant mortality to 3% (not significant). This holds true for preterm birth as well (Figure 5). When socioeconomic/structural factors are considered (dark blue dots), the odds of preterm birth for women living in a high concentration NHB neighborhood decreases from 10% to 0%. This is in line with previous research that has shown that neighborhoods with a high NHB concentration also have fewer resources, such as quality housing, healthy food options, and health care providers, all of which drive the effect.(8,9)

Figure 5: Preterm Birth Model: The Impact of adjusting for Socioeconomic and Structural Factors on the Effect of Racial Composition



Adjusted OR and 95% CI for effect of area-level NHB concentration on preterm birth for models including racial composition only and racial composition+socioeconomic/structural variables, Medicaid WRA cohort 2008-2015

Figure 6: Infant Mortality and Preterm Birth Model: The Effect of Socioeconomic & Structural Factors on Preterm Birth

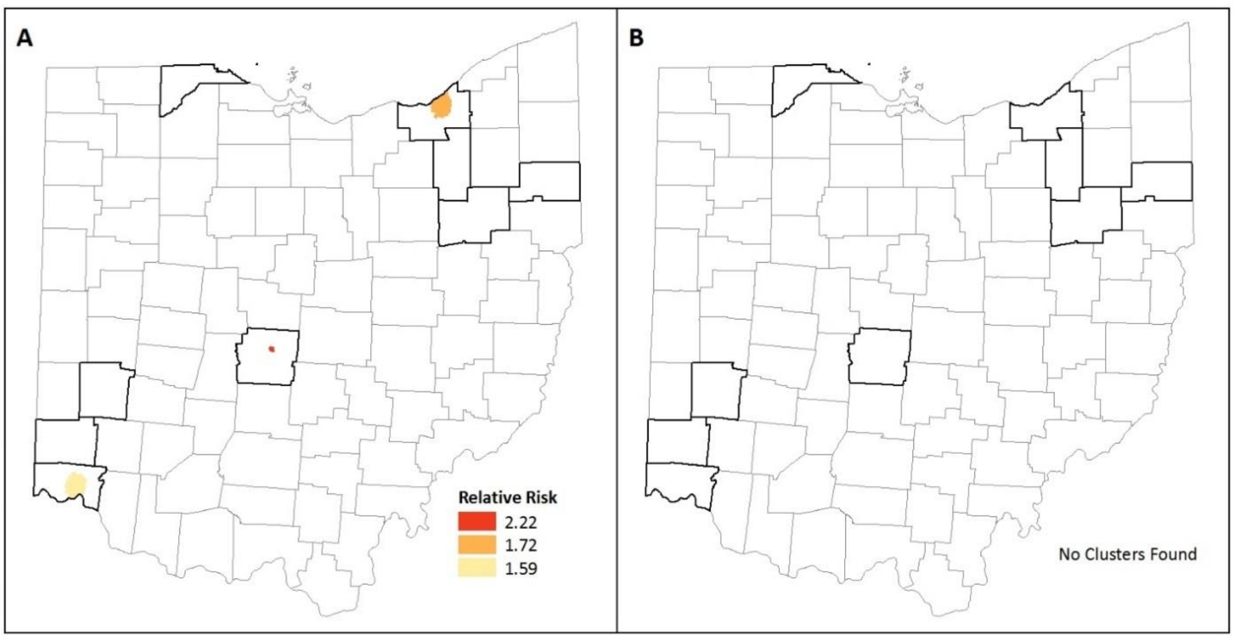


Adjusted OR and 95% CI for effect of area-level variables on infant mortality and preterm birth

Living in an Ethnically Isolated Community is Protective While Living in an Area with High Homicide Rates Increases Risk for Infant Mortality and Preterm Birth

While socioeconomic and structural factors mitigate the negative effect of living in a highly concentrated NHB area, these factors have very small independent effects on infant mortality and preterm birth (Figure 6). For example, living in an ethnically isolated community (e.g., high concentration of non-English speakers and a large foreign-born population) decreases odds of infant mortality by 5% (teal dots) and 2% for preterm birth (dark blue dots). Prior research suggests this may be because there is more social support in an ethnically isolated community.(10,11) Living in an area with a high homicide rate increased odds of infant mortality by 13% and odds of preterm birth by 5%. **There are spatial clusters of infant mortality in major cities that are the result of the spatial distribution of maternal age, race and education**. Figure 7 shows clusters of infant mortality in Cleveland, Columbus and Cincinnati (Panel A). These clusters disappear when the clusters are adjusted for maternal characteristics.

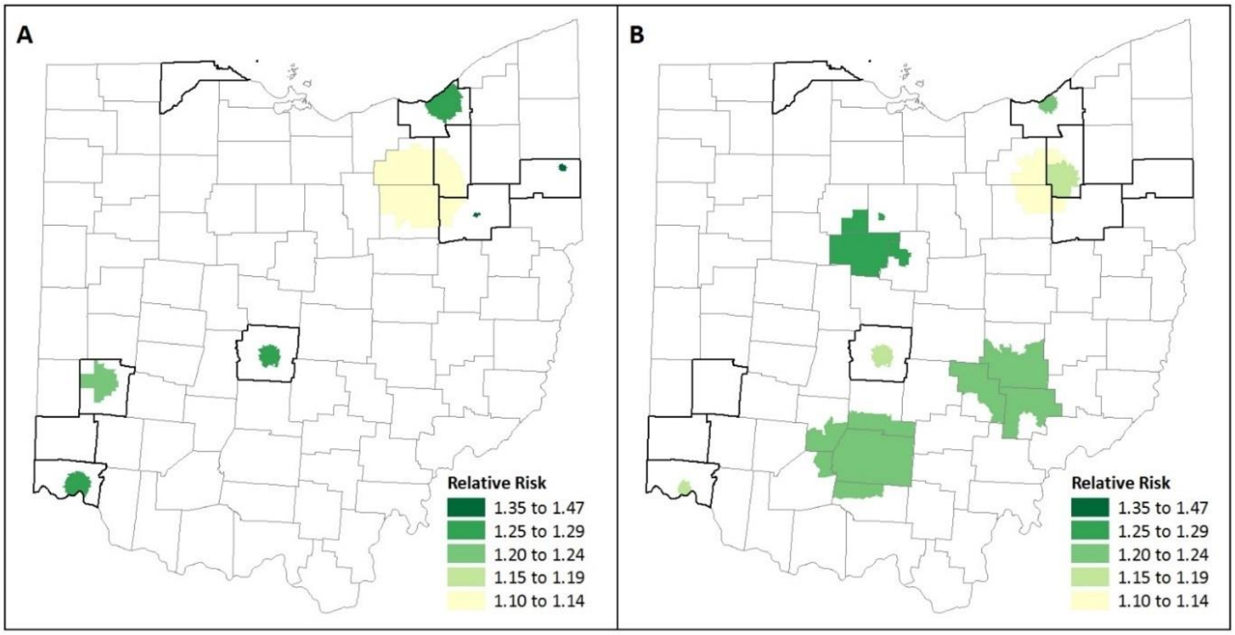
Figure 7: Spatial Clusters of Infant Mortality: A) Unadjusted and B) Adjusted for Maternal Age, Race and Education. Medicaid WRA Cohort 2008-2015



Spatial Patterns of Preterm Birth are Related to Other Factors in Addition to Demographics

Figure 8 shows clusters in Cleveland, Canton, Youngstown, Columbus, Dayton and Cincinnati. The clusters in Canton, Youngstown and Dayton disappear with adjustment for age, race and education, but clusters in Cleveland, Columbus and Cincinnati persist and new clusters appear in Appalachian counties and rural areas north of Columbus in the counties of Ross, Perry and Morgan. Targeted intervention may be necessary to address the higher than expected preterm rates in these rural counties.

Figure 8: Spatial Clusters of Preterm Birth: A) Unadjusted and b) Adjusted for Maternal Age, Race and Education, Medicaid WRA cohort 2008-2015



The Case Study of OEI Counties Shows That All-Cause Infant Mortality Rates Generally Declined Between 2008 and 2015, Mainly Driven by a Drop in Rates in 2015

OEI coalitions were formed in State Fiscal Year 2014 and the various interventions included very specific programs targeting pregnancy-related risks. For the most part the identified interventions were aimed at reducing premature and low birth weight births, as well as decreasing sleep-related deaths. These were appropriate as the cause of death analysis shows that premature and low birth weight births and sleep-related deaths accounted for 83% of deaths in these counties. It cannot be said whether the drop in death rates shown in Table 2 are due to these interventions, but it is clear that there was a drop in infant mortality after coalitions were formed.

Table 2: All-Cause Death Rates (Per 1,000) Calculated From Death Certificates Linked with Full Cohort Files at the County Level for OEI Counties

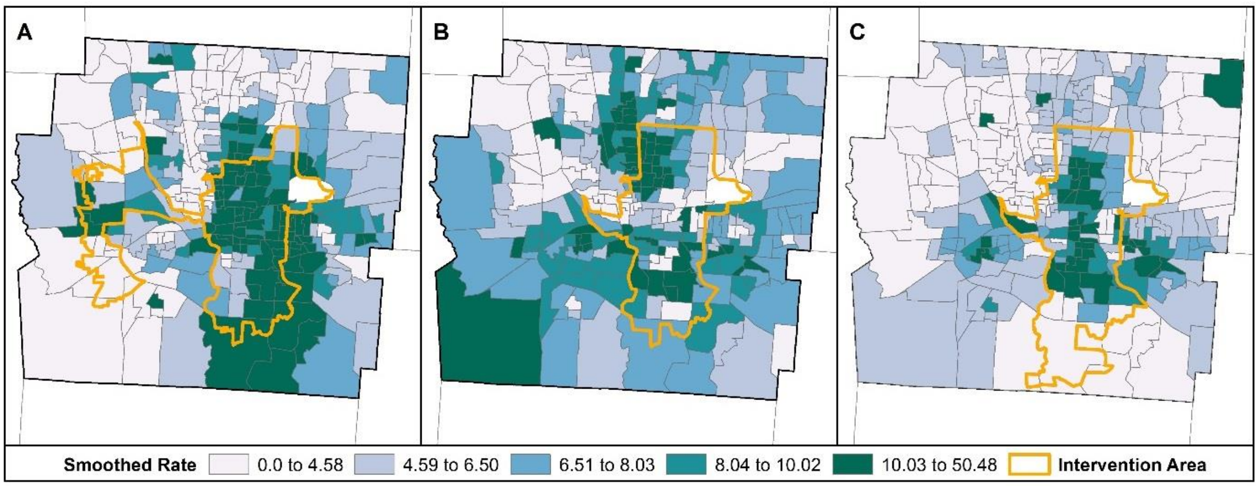
County	2008	2009	2010	2011	2012	2013	2014	2015
Butler	6.55	6.43	5.01	7.66	6.50	7.64	8.31	5.24
Cuyahoga	9.81	8.22	8.23	7.82	7.12	6.27	7.37	7.98
Franklin	7.44	7.86	7.34	8.45	6.75	7.08	6.90	5.11
Hamilton	10.5	8.81	9.80	8.48	7.43	6.98	7.28	6.49
Lucas	6.92	7.35	7.41	5.68	7.35	4.80	7.07	4.17
Mahoning	9.69	8.76	12.09	7.45	7.22	8.85	7.13	6.38
Montgomery	7.18	7.86	6.87	8.43	7.08	7.60	5.96	7.09
Stark	6.35	7.48	9.56	8.16	7.79	6.35	6.68	4.77
Summit	6.08	6.99	6.94	8.36	6.58	4.47	5.54	6.13
All OEI	**8.17**	**7.88**	**7.95**	**8.01**	**7.04**	**6.61**	**6.95**	**6.11**

The lowest annual rate per county is highlighted to show the general downward trend.

Micro-Level Analysis of the Franklin County OEI Shows a Geographic Shift in Programming and Corresponding Changes in Infant Mortality

Figure 9 reflects three separate time periods of interventions and infant mortality rates. The maps show the spatial reach of interventions shifted over time, with coverage in the west in 2008-2009 (panel A) (e.g. Women's Health Center West) shifting towards central coverage for 2010-2012 (panel B) (e.g. Moms2Be) and eventually reaching south in 2013-2015 (panel C) (e.g. PrimaryOne Health). There is evidence that these shifts in the geographic scope of interventions track, to some extent, with changes in infant mortality rates in the county over time.

Figure 9: Place Based Infant Mortality Interventions and Smoothed Infant Mortality Rate Maps (per 1,000 births) for A) 2008-2009, B) 2010-2012, C) 2013-2015



2.4 Implications/Conclusions

- **The spatial distribution of infant mortality within the Medicaid population in Ohio is largely driven by differences in population composition across the state.** The spatial clusters in the state are centered in large cities, in neighborhoods with concentrated NHB populations. The multilevel models support this and show that a good proportion of the Black-White disparity in infant mortality risk can be explained by neighborhood racial composition.
- **The OEI counties currently cover the areas with clusters containing high infant mortality, suggesting that the state is already appropriately targeting the highest risk areas.** The results of the case study of the OEI counties – which shows that the lowest rates of infant mortality across all causes of death occurred in 2015 after the implementation of many programs – suggest that the OEI programs may be working to reduce poor birth outcomes, though this design does not allow for causal inference regarding the effect of this targeted intervention strategy.
- **Efforts to reduce infant mortality in the state should continue to target OEI counties, and areas within those counties, having concentrations of**

disadvantaged NHB residents. At the same time, multilevel models suggest a few other potential points of intervention, most of which are related to the inequities in social and health services in NHB communities. For example, further investigation into the effects of neighborhood violence, poor housing, transportation availability, employment opportunities, and drug abuse will likely reveal additional opportunities for individual- and community-level interventions.

- **The spatial distribution of preterm birth is not entirely related to the distribution of the NHB population.** Spatial clusters persist in urban areas even after adjustment for maternal age, race, and education. Further, new clusters in rural areas were revealed. These rural areas are not currently a target of the OEI program, so a new focus on Ross, Perry and Morgan counties may be necessary to address the higher than expected preterm rates in these counties. The OEI counties were chosen specifically to address racial inequities. The data-informed approach used here shows additional *spatial* inequities that extend beyond the current reach of the OEI communities. Expanding efforts into areas outside OEI counties with higher than expected preterm birth rates would increase the overall population health impact.
- **Models suggest possible points of intervention for preterm birth.** Similar to infant mortality, reductions in neighborhood violence or exposure to violence may marginally improve preterm birth, as would poverty reduction strategies that target neighborhood factors such as poor housing, high unemployment and low education.
- **The case study suggests that tracking mortality rates over time, by geographic areas that have been aligned with intervention areas, can be useful in determining population health effects.** Essentially, this type of analysis can help policymakers determine if the programmatic offerings as a whole are impacting birth outcomes. Many programs in OEI counties target specific geographic areas and overlap, suggesting that the effect of one specific intervention will be very difficult to tease out. Evaluations that seek to use large-scale administrative datasets will need to carefully consider all the interventions and programs, and their geographic extent.

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SECTION 3: SYSTEMS MODELS OF INFANT MORTALITY IN OHIO

3.1 Introduction and Objectives

The IMRP recognized a need to study infant mortality, and interventions to reduce it, from a systems perspective. This study aimed to identify the mix of interventions predicted to reduce infant mortality in Ohio using System Dynamics (SD) modeling. Because financing is such an important issue, the models also present changes in funding scenarios and describe how funding can accelerate reductions in mortality. This study was limited to recipients of Medicaid within the State of Ohio.

3.2 Methods

SD modeling is a methodological approach for understanding the structure and analyzing the dynamics of complex systems.(2,3,4) SD modeling is an iterative process. The process followed in this project can be divided into three major phases: 1) group model building (GMB), 2) formulation and simulation of the model, and 3) calibration of the model with Medicaid data. GMB is a set of techniques to develop system dynamics models with direct involvement of clients.(5,6,7)

3.3 Key Findings

The findings can be separated into three domains, **1)** systematic understanding of how a conceptualization of infant mortality is altered through a systems modeling perspective; **2)** specific findings from the simulated models showing the impact of different interventions (at the population and individual levels) and **3)** an understanding of the fiscal costs and opportunities from making different policy choices.

3.3.1 Conceptualizing Infant Mortality

The same question which drives these models, drives strictly causal models: how can infant mortality in Ohio be reduced, especially for individuals from disadvantaged backgrounds or in geographic areas with high clusters of infant mortality, (e.g. the nine Ohio Equity Institute [OEI] communities)? For the initial GMB session in August 2016, the research team, with GMB participants, identified a list of policies and programs targeting individuals and communities that were either designed to or could directly or indirectly affect infant mortality. Figure 10 provides a visual representation of the GMB discussion. The group clustered the initial policies into four areas, **1)** long-acting reversible contraceptives (LARC) and progesterone therapy, **2)** housing and food policies, **3)** education policies, and **4)** Medicaid policies. This list reflects the combined knowledge of experts from medicine, public health, social science, and government. This expert-driven process complemented the systematic scoping reviews.

Moreover, when investigating the problem of infant mortality with the GMB team in August 2016 and again in March 2017, the role of social and economic factors that could impact infant mortality remained in focus. A key aspect of these activities was to provide opportunities for experts to develop working models of the social and economic attributes that would impact mortality. Figure 11 provides an early visual representation of a portion of one of the working models. It provides a straightforward way of representing the flow of women through pregnancy and birth, and separates out those with high and low medical risk.

Figure 10: Visualizing Policy Levers (from Group Model Building 8/2016)

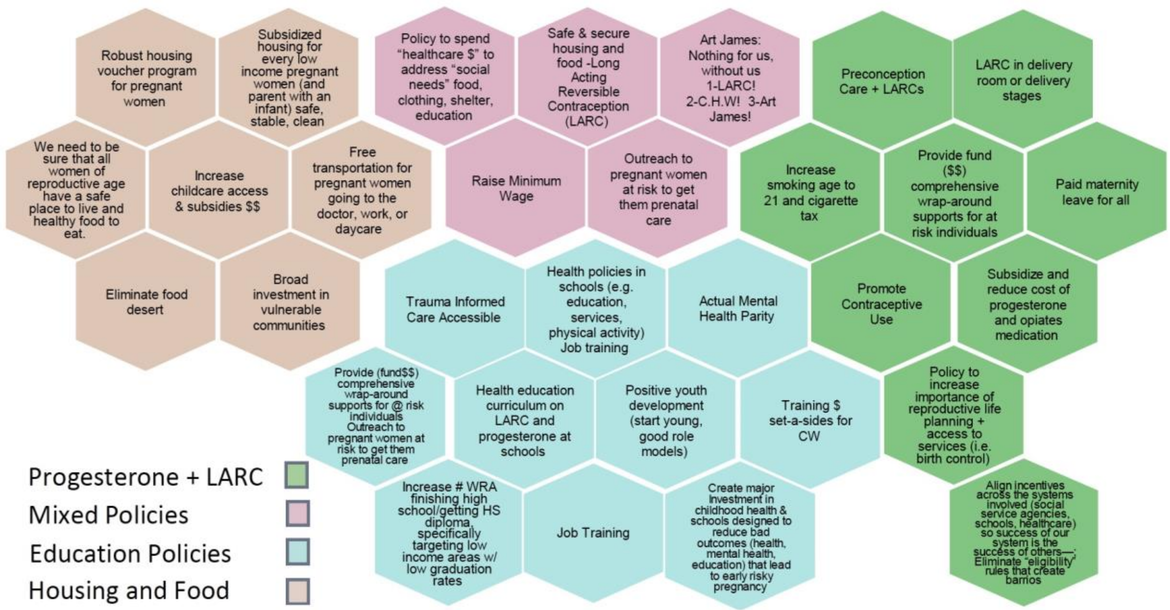
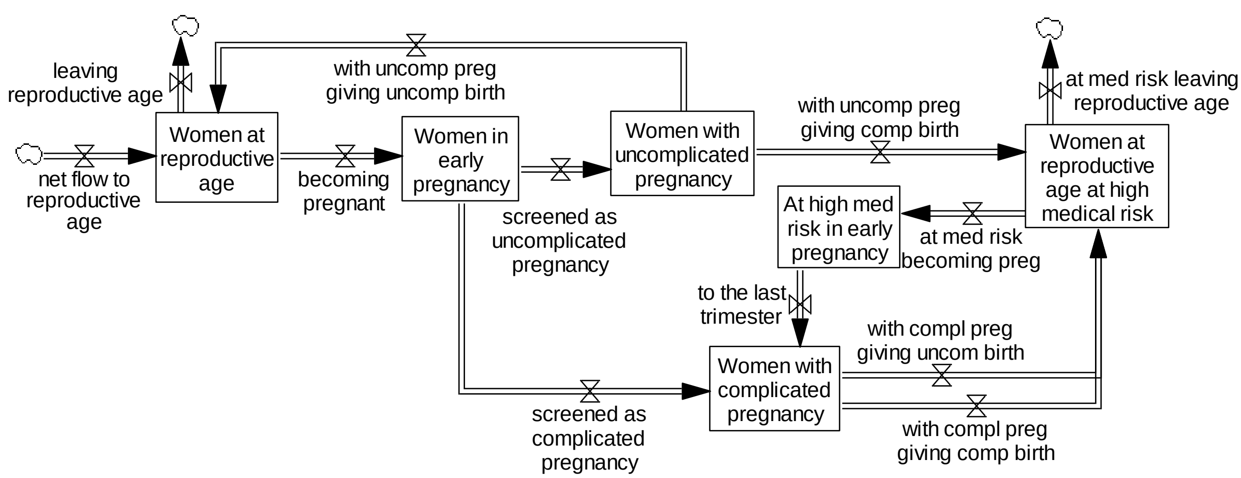


Figure 11: Early System Dynamics Model Representation of Women's Model

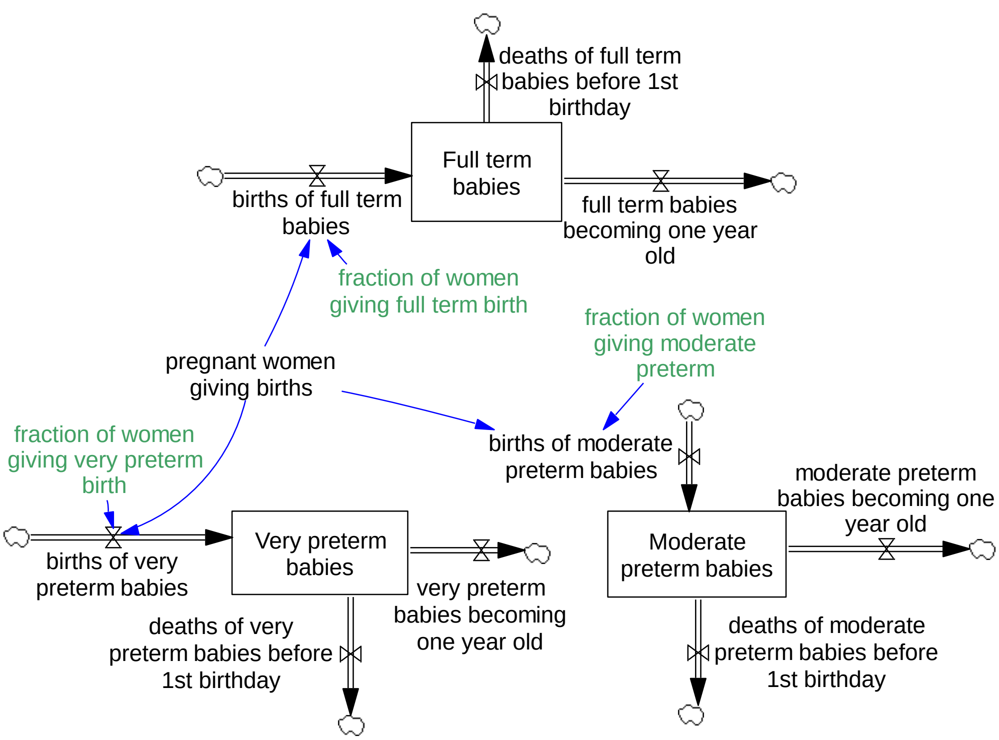


3.3.2 Specific Findings of Simulated Models

An SD model of infant mortality was developed for the state of Ohio to investigate the impact of different interventions on the IMR. A GMB exercise was conducted with subject matter experts and policymakers to capture the core structure of the problem. The focus was on Ohio's Medicaid population. The models developed from GMB output were calibrated using data provided by ODM. The SD model includes three sectors, *women*, *babies*, and *finance*. It incorporates two medical interventions, *progesterone therapy* and *LARCs*. Finally, it evaluates two financing methods, *stove pipe* and *capture and reinvest*. IMR and associated cumulative costs were reported for each scenario through 2025.

Babies born before 32 weeks of gestation account for half of infant mortality and their healthcare costs are significantly higher than full-term and late preterm babies.(8) As a result, babies are categorized by gestational age into three groups: full-term babies (born after 37 weeks), moderate preterm babies (born between 32 and 37 weeks), and very preterm babies (born before 32 weeks). Figure 12 shows the model structure. The structure has been adapted for four types of pregnancy-birth outcomes: *complicated pregnancy and complicated birth*; *complicated pregnancy and uncomplicated birth*; *uncomplicated pregnancy and complicated birth*; and *uncomplicated pregnancy and uncomplicated birth*. The fraction of women having a full-term birth, the fraction of women having a moderate preterm birth, and the fraction of women having a very preterm birth vary for each of these four categories.

Figure 12: The Basic Structure of the Baby Model



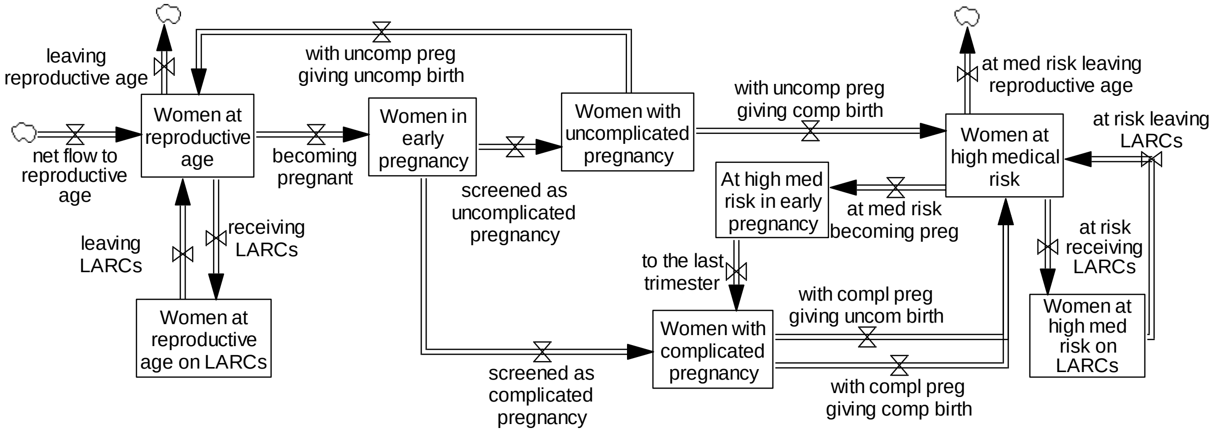
3.3.3 Financial Outcomes

Based on ODM data, currently, 23.7% of women at high medical risk use a LARC. It is not known what percentage of women eligible for the progesterone therapy currently receive it; as a result, the model was formulated with input from subject matter experts and a sensitivity analysis was conducted to estimate the range of IMR for different fractions of eligible women who receive progesterone. Simulation results show that providing progesterone therapy for all eligible women, while keeping the proportion of women using a LARC at their current level can reduce the IMR from 7.3 to 6.3 per 1,000 if 20% of eligible women currently receive it. Expanding progesterone therapy can reduce the IMR to 6.9, if 80% of eligible women already receive it.

Using the SD model, the costs of interventions as well as their benefits can be investigated. For example, the modeling shows that providing eligible women with progesterone therapy would reduce the IMR from 7.3/1,000 to 6.3/1,000, while increasing the total cost of progesterone therapy from $5 million to $17 million. The model assumes that progesterone therapy costs $500 per woman (Note: the cost of vaginal progesterone therapy was used to estimate the expenditure; the cost would be higher if injection were used) and LARC costs $1,000 per woman.(9-11) If progesterone therapy is financed through *capture and reinvest* - an investment strategy whereby savings from the reduction of costs in a program are reinvested to finance the program in the next period - the same IMR can be achieved at no additional cost. Funds for the *capture and reinvest* option are redirected from savings realized by reducing, among other things, a fraction of expensive NICU stays.

If the fraction of women at high medical risk using a LARC is increased from 23.7% to 50%, the IMR is reduced from 7.3/1,000 to 7.1/1,000, although the cumulative cost of LARCs increases from $50 to $109 million. While progesterone therapy reduces infant mortality by decreasing preterm births in high-risk women, using a LARC reduces both future full-term *and* preterm births. However, its impact on reducing infant mortality will be greatest among those women at high risk for another preterm birth, especially if their subsequent interpregnancy interval is short. In the SD model, the effects of using a LARC were modeled by preventing a portion of women at high medical risk from becoming pregnant, but the impact of increasing the interval between pregnancy for each individual was not modeled (Figure 13). The analysis shows that reducing unintended births with LARC results in a savings of **$15 million in direct medical costs**. Financing medical interventions, progesterone therapy and LARC usage, through *capture and reinvest* reduces IMR from 7.3/1,000 to 6.2/1,000 and leads to lower cumulative costs ($49 versus $56 million).

Figure 13: System Dynamics Model Representation of Women's Sector with LARC Intervention



3.4 Implications/Conclusions

The results from the study provide several suggested directions for state and local policymakers to consider.

- A primary takeaway from this team's methodological approach is the demonstrated value in engaging in community based participatory research, such as the GMB activity. This ensures the models are grounded in expertise across sectors, resulting in rich and robust models.
- Modeling the impact of interventions on the IMR should continue as the model will become more nuanced over time. Collectively revising the model at periodic intervals would enable state policymakers to adjust policy responses in a coordinated and responsive fashion.
- These initial models provide a useful foundation that can be expanded upon and further developed in future work. One example of how this work could be extended is through the modification of women and baby sectors; to better understand how other factors such as opiate abuse or child abuse and neglect interact with infant mortality. This might be continued by working with ODH, Ohio Department of Mental Health and Addiction Services (ODMHAS), or ODM to develop modeling priorities and to obtain additional data that can be added to the existing structure. Doing so will also expand the potential "toolkit" for stakeholders to reduce the IMR to include more state and local actors.
- Future work could also involve more extensive cross-methodological collaboration. For example, results from statistical predictive models could be incorporated to strengthen estimates of parameters in the systems models. Also, the systems models could be used to evaluate quality improvement programs in the health care system while taking into account organizational perspective of payers and providers.

- The models showed a definite impact of implementing progesterone therapy more widely and increasing the use of LARCs - both reducing births, and saving hospital costs for infants born prematurely.

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SECTION 4: PREDICTIVE MODELING: INDIVIDUAL PREDICTIVE MODELING OF PRETERM BIRTH AND INFANT MORTALITY

4.1 Introduction and Objectives

The goal of this section of the IMRP was to develop predictive models that could allow for personalized risk-prediction and improved communication between pregnant women and their healthcare providers. The principal study objective was to reduce the IMR for Ohio's Medicaid and at-risk populations by developing accurate, point-of-care predictive models that identify women and infants at high risk of suffering an infant death or of premature birth. The models incorporate data from time points throughout the course of pregnancy so, when used together, can allow for estimation of risk prior to pregnancy, in mid-pregnancy, and at birth.

4.2 Methods

To create the databases, death certificate information was merged with data from the birth certificates. The result was merged with the WRA study cohort, along with Managed Care Plans for mothers and babies at delivery.

Eleven logistic regression models were created. The models considered information available at three different timeframes: pre-pregnancy, early pregnancy, and postpartum. Using appropriate timeframes, the models examined four different outcomes: preterm birth, very preterm birth, 1-day mortality, and infant mortality. The same general modeling strategy was employed for all 11 models.(1) This report focuses on the Infant Mortality Model (model 11), which estimated the probability of an infant death using factors from all timeframes, and presents summary findings from models 1-5, which modeled factors from pre-pregnancy and early pregnancy (Table 3). The development, validation, and detailed discussion of the Infant Mortality Model and models 1-5, along with a list of all variables used and their prevalence in the population, can be found in the *Methodology Report*. Models 6-10 are available for use in the Infant Mortality Reduction Analytics Dashboard developed as part of the IMRP project.

Table 3: Outcomes and Timeframes of the Logistic Regression Models

Model #	Timeframe	Outcome
1	Pre-pregnancy	1-day mortality
2	Pre-pregnancy	Very preterm birth
3	Pre-pregnancy	Preterm birth
4	Early-pregnancy	Very preterm birth
5	Early-pregnancy	Preterm birth
11	All factors	Infant mortality

The Infant Mortality Model estimates the probability of infant mortality for an individual woman given characteristics included in the model. In addition, this study calculates the standardized mortality ratios (SMR) and associated confidence intervals for each county in Ohio (2). The SMR is defined as:

$$SMR = \frac{\text{Observed \# deaths}}{\text{Expected \# deaths}}$$

4.3 Key Findings

Figure 14: Odds Ratios (95% CI) for Predictors in Infant Mortality Model

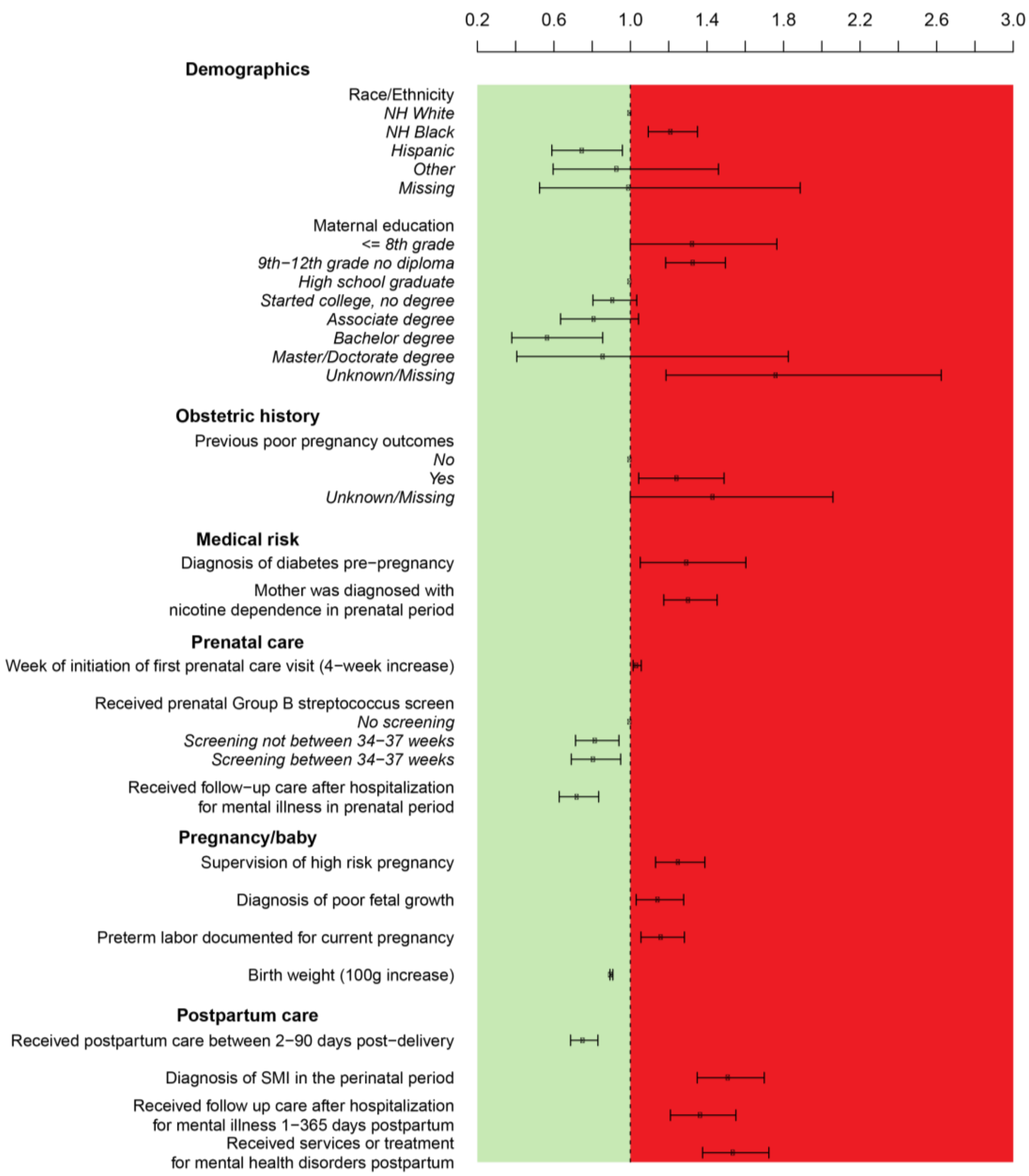
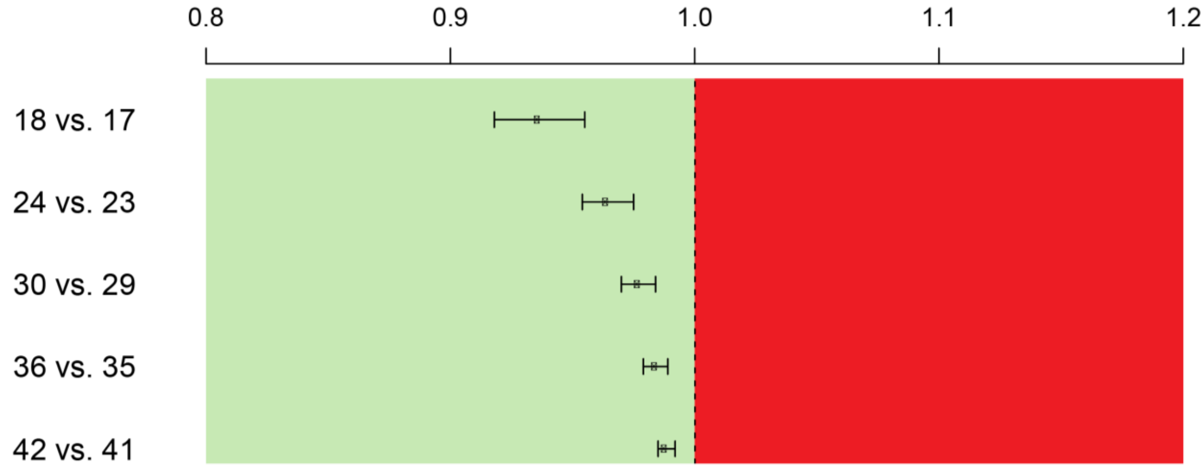


Figure 15: **Infant Mortality Odds Ratios (95% CI) for a One Year Increase in Maternal Age**



Infant mortality model based on the developmental dataset (N = 317,093). Odds ratios (OR) in green are considered protective, those in red suggest increased risk.
**SMI: Serious Mental Illness*

The variables included in the Infant Mortality Model, when used together, are a useful tool for estimating the probability of infant mortality for an individual woman. Each of these variables are associated with the outcome when adjusted for the other variables in the model. This does not imply that they are primary or *even secondary causes* of infant mortality. In fact, they may be proxies for factors that are causative. For example, the act of *supervising* a high-risk pregnancy is itself not likely to lead to infant mortality; rather, this variable is a proxy for the high-risk pregnancy itself. This model is not intended to investigate the effect of individual risk factors on the outcome, and should not be used as a way to determine which interventions would be helpful (e.g., it cannot be concluded that avoiding supervising a high-risk pregnancy will reduce the probability of an infant death). In light of these caveats, it can be useful to discuss the types of predictor variables in the model. The major risk factors highlighted in this model include:

Maternal demographics:

- NHB race/ethnicity and not having completed high school are each associated with increased odds of infant mortality.
- Increasing maternal age is associated with reduced odds of infant mortality. In particular, a one year increase in age is associated with a more important reduction of the odds for younger mothers than for older mothers.

Maternal comorbidities and health history:

- Diabetes diagnosed before pregnancy, current diagnosis of preterm labor, diagnosis of poor fetal growth, nicotine dependence and current supervision of high-risk pregnancy are associated with increased odds of infant mortality.

- Conversely, having timely postpartum care is associated with decreased odds of infant mortality.

Maternal mental health:

- Receipt of services or prescriptions for mental health disorders in the postpartum time period, diagnosis of severe mental illness in the prenatal period, and follow-up care after hospitalization for mental illness one year after delivery are associated with increased odds of infant mortality.
- In contrast, having follow-up care for mental illness after hospitalization is associated with decreased odds of infant mortality

Using the model described above, one can estimate the risk of infant mortality in an individual woman. For example, consider the two hypothetical women:

Case 1: The patient is a 28-year-old Hispanic woman presenting for prenatal care at 10 weeks gestation. This is her third pregnancy. She has had two prior vaginal deliveries at 38 and 39 weeks gestation of a boy and girl, both normally grown. Her last pregnancy ended 2 years ago, and she has been using low dose oral contraception. This pregnancy was planned. She reports that in her last pregnancy she was diagnosed with gestational diabetes at 30 weeks gestation. She followed the recommended program of diet and exercise and did well. The patient reports that she is married, and her family lives in a subsidized rental property. Her husband works in construction. She has never smoked or used drugs. She left high school in the 11th grade but has competed her G.E.D. and works as a nurse's aide in an assisted living community.

The patient's pregnancy proceeds uneventfully. She is found to be Group B strep negative at 36 weeks gestation. She delivers a 3500 gram male infant vaginally at 39 weeks gestation. The patient and her baby leave the hospital 36 hours after birth. She is seen in her obstetrician's office for follow-up 6 weeks after delivery and is doing well.

Case 2: The patient is a 19-year-old NHB woman presenting for prenatal care at 18 weeks' gestation. This is her second pregnancy. Ten months ago, her first pregnancy, resulted in a vaginal delivery at 26 weeks' gestation after the onset of spontaneous preterm labor. That infant, a boy, weighed 800 grams and spent 3 months in the NICU before being discharged home. The infant was found dead in his mother's bed at 4 months of age. The patient reports she was seriously depressed after that loss. She was told to see someone for this, but did not.

The patient explains that she left school in 10th grade. She has smoked since high school and continues to smoke. She denies substance abuse. The patient lives with her mother but reports that she has to move in with friends every few months. She is employed intermittently at a distribution warehouse.

The patient is offered weekly 17-OH progesterone injections to reduce her risk of recurrent preterm birth. She is also followed by a Maternal-Fetal Medicine specialist for her high-risk pregnancy. However she fails to attend clinic regularly because she is working and lacks transportation and receives only 2 progesterone injections. She is hospitalized for severe depression at 22 weeks, but misses her follow-up counseling appointment. At 28 weeks gestation, she delivers a 1000 gram female infant vaginally after the onset of spontaneous preterm labor. She did receive corticosteroids 48 hours before birth. The baby develops moderate respiratory distress syndrome (RDS) and remains in the neonatal intensive care unit (NICU) for 10 weeks before discharge home.

Using the Infant Mortality Model one can estimate the probability of infant mortality for each of these patients. For **Case 1**, one would use as model inputs the woman's age (28), race/ethnicity (Hispanic), week presenting for prenatal care (10), obstetric history (previous poor pregnancy outcome = no), education (High school degree), screening (GBS screening between 34-37 weeks), received postpartum care (yes), preterm labor (no), birth weight = 3500 g. These factors would give her an estimated **0.082%** probability of infant mortality.

For **Case 2,** one would use the woman's age (19), race/ethnicity (NHB), week presenting for prenatal care (18), obstetric history (previous poor pregnancy outcome = yes), education (9^{th} - 12^{th} grade, no diploma), birth weight (1000 g), mental health history (Received follow up care for hospitalization for SMI = no; diagnosis of SMI = yes), screening (GBS screening= no); preterm labor documented for current pregnancy = yes, nicotine dependence = yes, supervision of high-risk pregnancy = yes. These factors would give her an estimated **17.81%** probability of infant mortality.

The Infant Mortality Model should be used at the time of, or after a birth. The IMRP dataset contained a rich array of data that enabled the construction of a powerful model. However, other models developed in this study are designed to be used earlier in the course of pregnancy. These models can help to identify women at higher and lower levels of risk at a point where interventions may help to prevent preterm birth, itself a major risk factor for infant mortality. Table 4 shows how Models 1-5 (detailed in the *Methodology Report*) can be used to calculate the estimated probability of various outcomes using the factors available in the cases above.

Table 4: Estimates of the Probabilities of Case 1 and Case 2 for Models 1-5

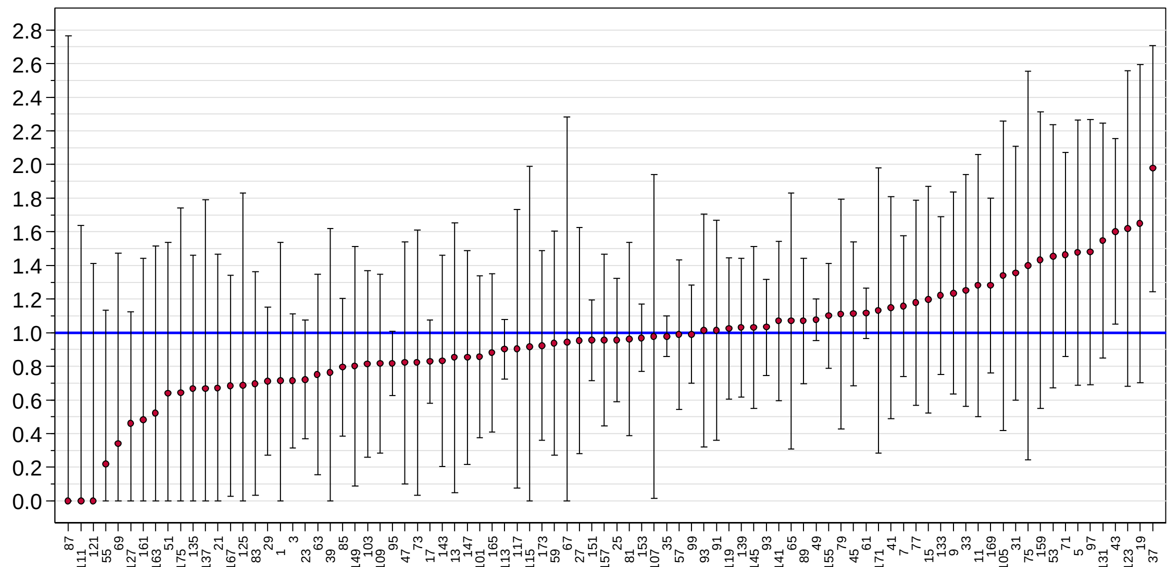
Model #	Timeframe	Outcome	Estimate of the probability for case 1	Estimate of the probability for case 2
1	Pre-pregnancy	1-day mortality	0.0682%	1.29%
2	Pre-pregnancy	Very preterm birth	0.754%	20.60%
3	Pre-pregnancy	Preterm birth	6.40%	44.74%
4	Early-pregnancy	Very preterm birth	0.364%	16.42%
5	Early-pregnancy	Preterm birth	5.72%	35.45%

The model itself should not be used to suggest specific interventions. However, the high probabilities of negative outcomes for the second case provide an objective measure of the patient's high-risk condition. Given that 0.57% of infants in the development dataset died, an estimated probability of almost 18% from the Infant Mortality Model is a highly significant risk. The patient in Case 2 would fall within the top quintile of risk in the dataset. Such high risks could be used as striking evidence in the prenatal counseling of the patient and could trigger the obstetrician to pursue more intensive interventions. In this specific example, the obstetrician might refer the patient for mental health and social support services earlier in the course of her pregnancy, ultimately leading to a healthier pregnancy and baby.

Figure 16 shows the SMR for all 88 counties in Ohio. Counties whose confidence interval lies completely below the horizontal 'unity line' have lower observed infant mortality than the model predicts, while those whose confidence interval lies entirely above the unity line have higher observed infant mortality than predicted by the model. This same type of analysis can also be done for other categorizations such as managed care plans.

The work presented here is only the first step to fully leverage the IMRP data for predictive modeling. This study provides strong evidence that these data can be used to reliably estimate probabilities of relevant infant mortality and pre-term birth outcomes. Future work could focus on incorporating additional covariates from other available datasets, using the models at the point of care to inform clinical practice, and testing these models on more recent data.

Figure 16: Observed to Expected Infant Mortality Ratio Across Counties, Ranked From Smallest to Largest Standardized Mortality Ratio



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SECTION 5: DISCUSSION

5.1 Putting Results into Context

The IMRP brought together three very different methodological approaches to large-scale data analysis toward addressing the problem of infant mortality in Ohio. These included spatiotemporal modeling, systems dynamics modeling, and individual predictive modeling. These modeling strategies addressed different levels of the socio-ecological model to provide a broader picture of infant mortality.

A principal value of this project lies in the tools that have been created for policymakers and healthcare professionals. These tools can help stakeholders investigate the causes of infant mortality, develop strategies to address these issues, and then simulate the outcomes of these strategies. This innovative approach gives policymakers a powerful analytics tool to make a difference in the lives of Ohio mothers and their babies.

There are several important themes to highlight in this report, presented here in terms of the level in which they fall within the socio-ecological model.

5.1.1 Individual Level

The Association Between Maternal Demographics, Infant Mortality, and Preterm Birth
Each year in Ohio, nearly 1,000 infants die before reaching their first birthday, and a disproportionately large number of them, nearly 40%, are NHB infants. This disparity is evident in the findings of the IMRP; however the results of the IMRP's work also show that this is a complex issue that deserves a more nuanced approach.

NHB race/ethnicity was associated with increased odds of infant mortality in the individual predictive model (Figures 14) even when adjusted for age, maternal comorbidities and obstetrical history. In fact, race was a significant factor in all 6 predictive models. Education was also associated with infant mortality in all of the models. In the Infant Mortality Model, detailed above (section 4.3), those without a high-school diploma or unknown educational history had the highest odds of infant mortality, when adjusted for all other factors in the model.

Similarly, the spatiotemporal model showed that spatial clusters are concentrated in urban neighborhoods with high concentrations of NHB residents. Compared to neighborhoods with <25% NHB residents, the odds of an infant death in neighborhoods with >75% were approximately 20% greater. The odds were increased for preterm birth as well. The multi-level models (see Table 2.8, *Methodology Report*) showed NHB race and not completing high school to be significantly associated with infant mortality.

Interestingly, spatial clusters of infant mortality in major cities disappear when adjusted for maternal age, race and education, suggesting a much more complex role of race in infant mortality. In contrast, premature birth clusters *do not* disappear in most large urban areas when models adjust for maternal age, race, and education.

The Association Between Prior Obstetrical History, Medical Complications, Infant Mortality and Preterm Birth

In addition to demographics and community-level factors, an individual woman's obstetric and medical history was also found to be associated with infant mortality.

Obstetrical History. The individual-prediction Infant Mortality Model (Figure 14) showed that supervision of a high-risk pregnancy, preterm labor documented for current pregnancy, and diagnosis of poor fetal growth were associated with increased odds of infant mortality.

Medical history. Medical and mental health history was found to be associated with infant mortality in the individual predictive models. Diabetes diagnosed before pregnancy and nicotine dependence were associated with increased odds of infant mortality (Figure 14).
Receipt of services or prescriptions for mental health disorders in the postpartum time period, diagnosis of severe mental illness in the prenatal period, and follow-up care after hospitalization for mental illness one year after delivery were associated with increased odds of infant mortality. In contrast, having follow-up care for mental illness after hospitalization was associated with decreased odds of infant mortality.

5.1.3 Organizational Level

The Association Between Access to Prenatal Care, Appropriate Postnatal Care, Infant Mortality and Preterm Birth

Progesterone. The systems dynamics (SD) model assessed the impact of progesterone therapy on infant mortality and explored the financial implications of increasing appropriate progesterone use. Specifically, the model suggested that reducing the IMR from 7.3 to 6.3 by increasing the appropriate use of progesterone therapy will increase costs of therapy from $5 to $ 17 million. However, if progesterone therapy is financed through *capture and reinvest* - an investment strategy whereby savings from the reduction of costs in one arena (reduction in PTB) are reinvested in another- the same IMR can be achieved at no additional cost.

Prenatal Care Initiation and Postnatal Follow-Up Care. The individual predictive models also showed the impact of pre- and postnatal care. The week of initiation of the first prenatal care visit was associated with the outcome of infant mortality (Figure 14) with a later initiation being associated with increased odds of infant mortality. In contrast, receipt of a prenatal Group B streptococcus screen (a possible proxy for adequate prenatal care) in the third trimester was associated with decreased odds of infant mortality. Conversely, having timely postpartum care was associated with decreased odds of infant mortality.

Long-Acting Reversible Contraceptives (LARC). One of the most effective ways to address the problem of infant mortality is better access to LARC. This can disproportionately decrease higher risk pregnancies such as those following short inter-pregnancy intervals. The SD model simulated the impact of reducing unintended births and suggested that this would result in a savings of $15 million in direct medical costs.

5.1.4 Community Level

The Association Between Social Determinants, Infant Mortality and Preterm Birth
Results showed that social factors such as housing and exposure to high crime areas are extremely important in influencing infant mortality. The spatiotemporal models showed that once area-level socioeconomic and structural variables are taken into account, much of the effect of living in a high concentration NHB area dissipates. These models also suggested that living in an area with a high crime rate increases the risk of infant mortality and preterm birth. This is a novel finding with significant implications for statewide interventions and policy.

5.1.5 Policy Level

The Impact of Ohio's Current Interventions on Infant Mortality and Preterm Birth
The IMRP's analysis of Ohio's current interventions is extremely encouraging. All-cause infant death rates declined from 2008-2015 in Ohio Equity Institute (OEI) counties. Many of the current strategies that the state is employing are the ones that appear to be most promising in the simulation models (e.g. progesterone therapy, LARC).

Gestational Age Findings
A large fraction of infant deaths occurred at pre-viable gestational ages. Specifically, analyses found that 13.8% (1,117/8,114) of infant deaths occurred before or on their 20th week of gestation. Infants born at such an early gestational age would not be expected to survive given limits to currently available medical interventions.

Ohio had the 7th highest proportion of infant deaths <20 weeks gestation (7.7%) according to CDC Wonder data from 2010-2014. When infant deaths less than 20 weeks are excluded, Ohio's IMR drops to 6.9 per 1,000 live births, compared to the reported 7.5 per 1,000. This issue has been discussed previously. A study of Ohio live births at 16-22 weeks gestation from 2006-2012 found that these births accounted for 0.25% of all live births, but 28% of all infant mortality for NHW newborns and 45% for NHB newborns.(1) In addition to the contribution to the overall IMR, the racial disparity in pre-viable live births may explain much of the IMR disparity between NHW and NHB infants.

On the policy level, these findings suggest that interventions aimed at decreasing preterm labor, (e.g. improving pre-pregnancy maternal health, early prenatal care, increasing inter-pregnancy interval) especially in communities at highest risk, will likely have a significant impact on both Ohio's IMR and in its racial infant mortality disparity.

5.2 Implementing the IMRP models

The work done by the IMRP is innovative. Instead of reporting static findings, the teams created dynamic and interactive models that can be used by policymakers and healthcare professionals to continue to investigate factors associated with infant mortality. The following are some (but not all) of the ways these models could be used to impact policy and care for individual Ohio women.

Identify high-risk areas in Ohio

- The spatiotemporal clustering allows policymakers to visualize areas at highest risk, as well as identify areas at high risk after adjusting for known risk factors. Once known risk factors are taken into account, counties in Appalachia are shown to be at increased risk.

Simulate the impact of interventions

- The models allow policymakers to assess the impact of population and individual level interventions to determine their likely impact.

Implement point-of-care individual models:

- Calculate individual risk: The final logistic regression models can be used in a calculator that can estimate the probability of an outcome (e.g., infant mortality) based on a woman's individual factors (see section 4.3). This could be used by a healthcare provider to help counsel an individual woman or by policymakers for hypothesis generation to consider which risk factors might be important to address.

Estimate impact of interventions:

- Estimate risk with changes in the prevalence of covariates: The predictive models (section 4) can be used to estimate the change in the probability of an outcome corresponding to changes in the level of a covariate. For example, if more women receive follow up care after hospitalization for mental illness, how might this change the expected number of infant deaths?

Assess performance:

- Use Standardized Mortality Ratios to compare counties and managed care plans**:** By calculating the SMR for counties and Medicaid managed care plans in Ohio, policymakers can more accurately identify counties that have lower or higher infant mortality than predicted.

5.3 Putting It All Together: The Infant Mortality Reduction Analytics Dashboard

The models discussed in this report have been incorporated into the Infant Mortality Reduction Analytics Dashboard to create a set of dynamic tools that can help users at ODH and ODM better understand and evaluate factors related to infant mortality in the state of Ohio. These tools were built in a web-based application so that they could be disseminated among the state sponsors to help inform policy decisions. In the future, certain functions of the dashboard could also be used by healthcare providers to assess risk in their patients at the point of care.

The dashboard incorporates geographic, systems dynamics, and individual predictive models. The geographic models allow users to visualize spatial clusters and relevant geographic layers of infant mortality on a map of Ohio, track the impact of interventions over time to decrease infant mortality, and identify high and low performing counties. Using the SD model, users are able to estimate the risk of relevant outcomes at the population level. Finally, the individual predictive models enable users to estimate the risk of relevant outcomes for individual women and infants over the course of pregnancy, and display standardized infant mortality rates for each managed care plan. For more information, please visit grc.osu.edu/projects/IMRP.

5.4 Strengths of the Partnership

This partnership was an innovative approach to large-scale data analytics to address a significant public health issue. The strengths of this approach included:

- **Robust methods:** Results and common themes can be compared across multiple, established methods to further assess the robustness of the findings.

- **Inter-institutional collaboration:** Subject matter experts and researchers from six of Ohio's major universities actively participated and collaborated throughout the process.

- **Ongoing communication and feedback:** Regular in-person meetings, conference calls, and webinars enabled the research teams as well as ODM, ODH, ODHE and GRC to provide continued constructive criticism and feedback.

5.5 Limitations of the Work

Due to the nature of this type of research, there were some challenges that were encountered during the course of the partnership:

5.5.1 Data Limitations

The IMRP leveraged data collected for operational and public health uses throughout the state of Ohio. As with any project that re-uses data collected for other purposes, there were expected and unexpected challenges related to data accuracy and completeness.

5.5.1.1 Missing and Inaccurate Data

There were discrepancies between similar variables among datasets used by IMRP researchers. For example, birth weight was available from multiple data sources, sometimes with different values for the same birth. There were also discrepancies between the date of death across some of the datasets. These are common challenges when using data collected for other purposes; however, they complicated the process of linking the data to additional files. This issue was exacerbated by the lack of a unique, cross-dataset woman and baby identifier (e.g. Social Security Numbers are not available within all study datasets). One of the IMRP's ancillary contributions was exploring some of these data issues to facilitate future work in this area.

In addition, some of the variables within data sources were not reliably collected, including those about important topics such as smoking cessation and breastfeeding support, and thus could not be used in the analyses.

5.5.1.2 Completeness of the Datasets

Despite a wealth of data available to project researchers, there are some risk factors across all levels of the socio-ecological model that are not easy to capture. For example, at the individual level, data were not available for measures of women's stress levels, their trust in the healthcare system, or their perceptions and experiences of racism. At the interpersonal level, data were not available for what kind of family or peer support women receive. At the organizational level, data were not available about women's interactions with mental health care providers or social service agencies (e.g. how hard it is to obtain help from organizations). From the community level, data on homicide deaths were available as a proxy for violence in the community, but overall crime rates were not available. Data about clean air and water and 'walkability' of women's community were not available in this phase of the project. Finally, at the public policy level there were insufficient data or results from prior studies on the impacts of housing policies, safety net policies, institutionalized racism, and changes in the healthcare system on infant mortality, PTB, or their antecedents.

In addition, available datasets were limited to live births. This limited the study's ability to model poor pregnancy outcomes in the state of Ohio.

5.5.2 Dynamic Risk Factors

The factors influencing infant mortality are dynamic, and some are changing rapidly and without high quality data that allow integrating them in models. Phenomena such as Medicaid expansion and the opioid epidemic in Ohio pose challenges to constructing and validating models such as those presented in this report. To address this challenge, ongoing modeling and engagement between researchers and policymakers will be essential.

5.6 Recommended Next Steps

The IMRP aimed to use Ohio's data to better understand infant mortality in Ohio and to develop tools to inform policy and practice. There are many ways that the results mentioned in this document as well as in future IMRP work may inform policy and interventions. A few of these include:

- While each county, census tract, and neighborhood share common challenges, each is also unique and will require locally-informed interventions.
- The research teams collectively demonstrated the importance of addressing the social determinants of health in resource-scarce communities if infant mortality is to be reduced. These include, but are not limited to: violent crime, food security, education, safe sleep programs and access to health care for women and children before, during and after pregnancy.
- Expanding and integrating mental health care services with perinatal medical care to address the strong association between serious mental health conditions and infant deaths.
- While these results have clear implications for policymakers and community leaders from many disciplines (e.g. housing, business, justice department), the findings from the IMRP could also be disseminated to practitioners to improve their practice at the individual

level. Health and social service professionals could benefit from translational science in this regard, in order to ensure they are equipped with a robust understanding of the multiple, intersecting factors contributing to infant mortality. This could ensure they are able to appropriately and effectively identify and address some of the factors impacting infant mortality, or mobilize the necessary community resources if needed.

- Expanded data collection: The IMRP researchers identified several risk factors that were not well represented in the dataset. This may have been because the data are not currently collected or that they just were not available in the datasets for the project. Some examples include:

    - State crime data at a neighborhood or census tract level.
    - Data on exact location of section 8/federal housing.
    - Air and water quality data. These are available but are time intensive to process for modeling.
    - Noise and urban greenness data.
    - Records reflecting fetal death or pregnancy loss that would give a broader picture of infant mortality and maternal health in Ohio.
    - A single unique identifier across all datasets for mothers and babies to avoid the challenges of probabilistic linking.
    - All residential addresses not just annual addresses.
    - Qualitative information from the Fetal Infant Mortality Review.
    - Walkability scores of Ohio streets and traffic counts.
    - Immigration status in history (important to address disparities among refugee, recent and long-term immigrants).
    - Opioid overdose rates at the census tract level.

The addition of these variables in future IMRP work would likely give a more accurate representation of the environment in which women in Ohio live.

While the infant mortality rate in Ohio has recently been reduced, it remains a significant public health problem. The findings in this report and other IMRP outputs provide insights and direction to focus and enhance efforts aimed at reducing the number of infants in Ohio dying before their first birthday.

5.7 References

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Abbreviations: CWRU: Case Western Reserve University; GRC: Ohio Colleges Of Medicine Government Resource Center; NEOMED: Northeast Ohio Medical University; NCH: Nationwide Children's Hospital; OSU: The Ohio State University; OU: Ohio University; UC: University of Cincinnati; VT: Virginia Polytechnic Institute and State University; WSU: Wright State University; PI: Principal Investigator; PM: Project Manager; C: Coordinating; G: Geospatial; I: Individual Predictive Modeling; P: Population Predictive Modeling; S: Systems Dynamics.