An Evaluation of the Maryland Maternal, Infant, and Early Childhood Home Visiting Programs

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Abstract: Home visiting is a social service aimed at improving the lives of prenatal and postnatal mothers of infant children, ages 0 to 5. Home visiting utilizes a curriculum of strategies designed to reduce internal stress related to parenting, and reduce external stress (specifically those resulting from poverty) by referring clients to existing outside agencies. Randomized control trials (RCTs) evaluating home visiting programs' impact on reducing stress have revealed mixed evidence of their effectiveness. Specific outcomes, like improved child cognitive abilities and improved maternal parenting skills, have been observed in some evaluations, but not in others (Duggen et al., 1999) (DuMont et al., 2011). Most RCT evaluations of home visiting measure program effectiveness by comparing average program impacts for a treatment and control group at pre-determined follow up periods, usually in 6 month increments. This analysis utilizes regression techniques to measure the number of home visits necessary to achieve a desired outcome for a mother or child. Under the Affordable Care Act, which established federal funds for certain home visiting programs, data reporting requirements were attached to home visiting programs receiving federal funds. In Maryland, the Department of Health and Mental Hygiene (DHMH) is tasked with disbursing these federal funds and maximizing the effectiveness of the home visiting programs receiving those funds. DHMH also collects and stores the data used in this analysis. Because the data only contains participators, estimates are only applicable to members of the sample. However, future analyses could utilize this model with a sample including participators and non-participators to obtain unbiased population estimates. Unbiased estimates of the relationship between the number of home visits and measured outcomes would allow policymakers and program staff to make informed decisions about how many home visits clients might need to improve their outcomes. Specifically, for each mother and child whose outcomes (See Table 4) are measured with an assessment tool, this analysis will provide a model which could estimate how many home visits would be necessary to raise that baseline assessment score to a desired level by determining the slope relationship between the number of home visits and that set of outcomes.

Introduction

In 2010, the Patient Protection and Affordable Care Act established federal funding for evidence based home visiting programs in every state through a program called the Maternal, Infant, and Early Childhood home visiting program (MIECHV). Home visiting is a preventative health and social service hybrid, where a paraprofessional or registered nurse meets in person with "at risk" prenatal and postpartum mothers in their home and delivers services to the mother and her children. "At risk" status is determined in two ways, and these methods establish eligibility criteria for MIECHV funded home visitation services.

First, mothers are considered eligible based on where they live. Maryland administered a state wide needs assessment that identified 15 indicators, measured by the U.S Census, as evidence of poor health and social outcomes (See Table 1):

Table 1: Indicators for geographic risk

Risk Factor	Maryland Average (2000 Census Data)

Abuse & Neglect Investigation Rate	1.6
Crime Rate	4316.5
Infant Mortality Rate	7.9
Medicaid Enrollment Rate	112
Percent Families in Poverty	9.5%
Percent Late or No Prenatal Care	4.3%
Percent Low Birth Weight	9.3%
Percent Preterm Births	11.2%
Percent Ready to Enter School	81%
Percent Unemployed	7.0%
Substance Abuse Treatment Rate	7.1
Teen Birth Rate	33
WIC Participation Rate	16.8

Source: (DHMH, 2011)

The needs assessment identified risk geographically, by flagging a zip code (or Community Statistical Area (CSA) for Baltimore City) as "elevated" for every indicator that was at least 1 standard deviation above the state mean for that indicator. Zip codes (and CSA's) in Maryland where at least 10 indicators were "elevated" were given funding through the MIECHV legislation; additional funding later expanded funding to zip codes with 7 or more elevated indicators (DHMH, 2010).

The second method for assessing "risk" for mothers is via an assessment tool (such as the Parenting Stress Index (Kemp et. al, 2008)) that asks mothers questions about their mentality towards parenting, their own life experiences, and their living conditions. The exact tool used to determine the degree of risk facing a potential client differs by jurisdiction. Women with scores that meet certain criteria for risk, based on the assessment tool, can be referred to home visiting programs. Home visiting programs across the United States receive funding from a variety of sources, however this paper will focus only on clients receiving home visiting services in Maryland through MIECHV funding.

Home visitors use activities and strategies from various program curriculums designed to improve a variety of health and social indicators for mothers and their children. Home visitors typically have supervisors and support staff that meet at an office location for administrative purposes, such as storing data collected during home visits, and strategizing to meet the needs of enrolled families. Home visiting office locations, called "sites", must earn accreditation from national home visiting program models by collecting certain data and demonstrating fidelity to that program model. The requirements for accreditation vary by program model. The home visiting programs funded by MIECHV are voluntary, and are therefore separate and different from any court ordered programs. Each office (and any supervisors) typically choose which home visiting program model, or curriculum, their home visitors implement during home visits, however to receive MIECHV funds, program sites must choose an evidence based model.

The United States Health Resources and Services Administration (HRSA) designates home visiting models as evidence based by using a meta-analysis of existing research on the available home visiting program models. (Health Resources and Services Administration, 2015). Maryland's MIECHV program funds primarily a program called Healthy Families America (HFA), an evidence based home visiting program which describes itself as an organization that attempts to improve child health and development, prevent child abuse and neglect, and promote positive parenting practices (Healthy Families America, 2015).

A simple description of the complex HFA program curriculum is that it attempts to help mothers and infant children in adverse conditions by reducing the stress in their lives. It is different from the Social Work profession in that home visiting is specifically designed as an in home meeting for prenatal mothers or mothers of very young (ages 0 to 5) children, and it specifically includes demonstration of appropriate parenting techniques and strategies to primary caregivers.

More broadly, home visiting is similar to teaching. Teachers (and home visitors) implement a curriculum with specific learning goals for the mother and for her child after it's birth. Different home visiting program models are available, each with different program goals. These programs function in the same way that a curriculum functions for a teacher. A teacher can choose among several different curricula to teach content. For example, consider a 7th grade English course. Depending on the curriculum (program model), the 7th grade English course may have a scripted curriculum where the teacher simply reads a prepared lesson plan that follows a logical progression through the subtopics taught in the 7th grade English course. Other 7th grade English curricula may offer the teacher the lesson plans, but allow the teacher to choose the order in which those lessons are taught and how those lessons are structured. Some 7th grade English curricula may provide activities for the teacher, but allow the teacher to write their own lesson plans and create their own daily class structure entirely. Home visiting programs can choose among a variety of home visiting program options that their home visitors will "teach" to mothers and their children, and the content taught during each home visit depends on program model being used by the home visitor.

Continuing the teaching analogy, HFA is most similar to the curriculum that is loosely structured, allowing teachers (home visitors) the ability to choose the lesson plan and activities for each home visit. While this may appear to give autonomy to home visitors and program supervisors to choose the content of each home visit, some literature argues that more structured home visits have produced greater benefits to enrolled mothers and children (Daro et al., 2003).

The MIECHV legislation mandates that all home visiting sites receiving MIECHV funding collect and submit certain data to the agency tasked with disbursing MIECHV funds. In Maryland, this agency is the Department of Health and Mental Hygiene (DHMH). The data collected includes the health and social outcomes that HRSA believes home visiting can affect. The outcomes were identified through HRSA's meta-analysis.

The data requirements are organized into six legislatively mandated benchmark areas, each with a definition of improvement: 1) Improve health and development; 2) Prevent child injuries, child abuse, neglect, or maltreatment, and reduce emergency department visits; 3) Improve school readiness and achievement; 4) Reduce crime, including domestic violence; 5) Improve family economic self-sufficiency; 6) Improve the coordination and referrals for other community resources and supports (Health Resources and Services Administration, 2015). Within each of the six benchmark areas, the MIECHV legislation required each state to create variables that would measure progress towards the benchmark goals.

Maryland created a set of survey instruments, called assessments, which are utilized by home visitors at MIECHV funded sites at pre-determined intervals. The intervals are based on either time in the program (called enrollment and post-enrollment assessments), or on time since the child's birth (postpartum assessments). Certain questions from these assessments are used to meet HRSA's data reporting requirement that indicates progress or lack thereof towards improvement in the six legislatively mandated benchmark areas.

While useful for measuring improvement within legislatively mandated benchmark areas, the MIECHV outcome data does not explain the mechanisms through which home visiting helps mothers and children. Mostly, these mechanisms attempt to reduce stress for mothers and their infant children by improving the parenting knowledge for the mother, which theoretically make the day to day parenting less stressful and improve the life of the child. They also refer clients to outside agencies for external stresses related to poverty. Outcome data used in this analysis measures the degree to which home visits affect the mother and the child's internal stressors.

Home Visiting: Rationale and Mechanisms

Many of the social and health programs that exist in the United States attempt to support women and young children who experience adverse conditions like poverty, poor maternal and child health, and abnormal child cognitive and social emotional development. Starting in the early 2000's, it was common for communities to establish systems to detect developmental delays, initiate well baby visits with doctors, and establish prenatal care systems that targeted women facing adverse conditions (Daro, 2004). These systems came in response to growing concerns about the affect of adverse conditions on pregnant women and the eventual impact of those conditions on their children.

There is ample research pointing to pregnancy and the first three years of a child's life as critical to brain development. A report from the Carnegie Corporation highlights five broad findings from research that illustrate the importance of this early development. During the first three years of life: 1) Brain development is extensive and rapid. 2) The brain is heavily influenced by events in its surrounding environment. 3) The environment's effects on an infant's brain are long lasting. 4) The environment shapes the number of brain cells developed, how those cells are connected, and how well those connections work. 5) Negative stress can impact a brain even during early infancy (Carnegie Corporation, 1994). Poverty, health concerns, and lack of safety are examples of adverse conditions can cause stress for mothers and children. Stress has a profound impact on the human brain, both for the primary caregiver, but especially for the developing brain of an infant.

Stress can have positive effects, but only under certain conditions. For infant children, stress can be positive if the parent provides appropriate attention to the child's stresses by responding to the child's needs (Middlebrooks & Audage, 2008). Providing for a child when it signals a need is an example of the "serve and response" relationship between parents and infant children (Center on the Developing Child, 2008). Examples of serve and response interactions include feeding, holding, playing games, and speaking/reading to the child, both when prompted by the child and when the mother initiates the connection.

When repeated frequently, these serve and response interactions are experiences that build a healthy architecture for an infant child's brain, by increasing the size and efficiency of the brain, and by assuring the child that it's needs will be met and that the primary caregiver can be trusted to consistently meet those needs (National Scientific Council on the Developing Child, 2012). However, if a child's attempts are not returned in a consistent, repeating manner, this can prevent the growth of the child's brain. Repeated lack of a "return" to a child's "serve" is called child neglect. There are several types of child neglect: "(1) physical or supervisory neglect (i.e., failure to provide adequate food, shelter, hygiene, and/or appropriate oversight to ensure a child's safety); (2) psychological neglect (i.e., failure to attend to a child's emotional and/or social needs); (3) medical neglect (i.e., failure to secure adequate treatment for an identified health problem); and (4) educational neglect (i.e., failure to meet a child's formal learning needs)" (National Scientific Council on the Developing Child, 2012).

Child neglect is the most common form of child maltreatment in the United States, according to the National Child Abuse and Neglect Data System (NCANDS). In 2013, almost 80% of all child maltreatment cases from the NCANDS system were characterized as child neglect, with roughly 18% child abuse cases, and roughly 9% sexual abuse and 9% psychological abuse (HRSA, 2013). Therefore, attempts to reduce child maltreatment must address neglect, and this can be accomplished through a home visiting intervention that strengthens the parent child relationship.

The policy implication of existing research on early childhood brain development indicates that early interventions are more effective than interventions that occur during adolescence and are also less costly (Center on the Developing Child, 2008).

The consequences of child neglect can persist into adulthood. Chronic and/or intense stress during childhood can impede the healthy development of the immune system, stunt cognitive development, and has been show to lead to alcoholism, heart disease, cancer, eating disorders and depression later in life (Middlebrooks & Audage, 2008) (Center on the Developing Child, 2008). Other longitudinal research following victims of childhood neglect into adulthood found that child neglect has been linked with lower adult IQ, lower probability to graduate high school, and poorer reading skills compared to adults who had not been neglected as children (National Scientific Council on the Developing Child, 2012). Child neglect is in part a function of the parent and child's relationship. Home visiting attempts to address both the external and internal stress that exists for mothers and children.

The foundation of a mother and child's relationship relies on the parenting skills of the mother, but these skills are affected by the stress and previous life experiences of that mother (Center on the Developing Child, 2008). This implies that parents do not always intentionally harm their child. In some (or perhaps many) cases, a very young mother may lack knowledge of best parenting practices. In other cases, the mother herself may have experienced stress, abuse and/or neglect during her own childhood, which means she may not have a frame of reference for what healthy parenting practices look like. This means that, in cases where parents lack knowledge, they need to be taught how to establish a consistent serve and return relationship with explicit demonstration. Home visiting is designed to demonstrate those skills. Yet focusing solely on the serve and return relationship from the child's perspective ignores the needs of the mother, who cannot provide such a relationship without the capability to do so. A big part of a mother's parenting capability is her stress.

The adverse effects of a poor parent child relationship on brain development directly affect the child's ability to succeed in life. Research has shown that children who enter school from a situation where they are behind in terms of basic vocabulary and math skills are less likely than their peers to achieve academic success (Child Trends Data Bank, 2012). Basic vocabulary and math skills can be taught to an infant child through basic reading and activities by a primary caregiver, and that parent's efforts have documented positive affects for that child (Duursma , Augustyn , & Zuckerman , 2008). These are activities that are modeled during home visiting sessions. In the long term, children who enter school with a higher level of basic vocabulary, reading and math skills are correlated with greater success in later years of school, greater probability to achieve higher levels of education, and are more likely to be employed (Child Trends Data Bank, 2012).

The reduction of stress and adverse experiences positions home visiting as an intervention that has the potential to generate a large return on investment. For example, as previously mentioned, children that enter preschool from families where they have given basic reading and math skills through vocabulary building and other activities are more likely to be successful in school, and are more likely to complete more years of school than neglected children (National Scientific Council on the Developing Child, 2012). Research has also shown that additional years of education, and more specifically college and postgraduate degree attainment, are associated with higher earnings (Federal Reserve Bank of San Francisco , 2015). The data used in this paper are limited to an approximate three-year panel, so long term benefits cannot be assessed directly. However, the Washington State Institute for Public Policy (WSIPP) assumes in its benefit cost analyses that measured effects can be indirect: short term outcomes can reasonably lead to long term outcomes, should strong evidence of intermediate outcomes be measured. The assumption of this progression of benefits over time is one basis for believing in home visiting's effectiveness.

Home visiting is designed to reduce stress for a primary caregiver and their child both through the home visiting curriculum and by connecting families to existing outside agencies. However, existing literature on HFA home visiting programs reveals that the design of the program does not consistently match how it works in practice. While the theoretical mechanisms through which home visiting helps mothers and children seem logical, the measured benefits of those mechanisms have not matched their intent.

Literature Review

Traditional Home Visiting Evaluations

Home visiting programs are typically evaluated with randomized control trials (RCTs), where average program impacts for treatment and control groups are compared to determine if the average treatment impact is statistically greater than the average control impact. The specific impacts measured across home visiting evaluations vary, but are typically similar across broad themes (See Table 2 for typical outcome areas). However, this type of comparison cannot accurately measure the quantitative relationship between program inputs and measured program outcomes, unless regression analysis is utilized. For example, RCTs cannot measure how increasing the number of home visits is quantitatively associated with an increase or decrease in an enrolled child's cognitive abilities. This analysis attempts to determine slope relationships for several outcomes in the Maryland MIECHV data set, which would be useful for MIECHV program staff and policymakers interested in determining how many home visits any particular family should receive in order to achieve desirable outcomes. Previous literature, using the RCT methodology, has found statistically significant improvements at certain follow up periods, but these are average improvements for average clients. This analysis will allow policymakers to take baseline measurements in outcome areas of interest, and make reasonable predictions regarding how many home visits would be necessary to improve baseline outcomes to desirable levels.

This analysis is not claiming that RCT methodology is useless. It does indicate which outcomes for mothers and children are statistically significant over a control group. Knowing which outcomes are statistically significant in a RCT is a prerequisite to estimating the slope relationships between program inputs and measured program outcomes.

HFA has been evaluated in many randomized control trials (RCTs), and the results indicate that the model does not consistently benefit mothers and children in the same way, as indicated by measured outcomes (Health Resources and Services Administration, 2015). In these RCTs, the treatment group receives referrals to agencies outside of the home visiting program for immediate needs like a positive depression screen, housing assistance, and cash assistance (to name a few), and also receives the home visiting intervention. The control group also receives referrals to existing outside agencies for immediate external needs, but does not receive a home visitor or home visiting services of any kind.

One seminal study incorporated in HRSA's meta-analysis is Duggen et. al's evaluation of Hawaii Healthy Families, the prototype of current national HFA program model. The authors found statistically significant impacts in the treatment group over a control group in 5 measured variables, but no statistical difference in 11 other variables. Specifically, measured at 1 and 2 year follow up periods, statistically significant positive impacts were found for the following measured program outcomes: improving maternal parenting efficacy, decreasing maternal parenting stress, promoting the use of nonviolent discipline, and decreasing injuries resulting from partner violence in the home. However, no positive impacts were observed in other variables, such as: the adequacy of well-child health care; maternal life skills, mental health, social support, or substance use; child development; the child's home learning environment or parent-child interaction;

pediatric health care use for illness or injury; or child maltreatment (according to maternal reports and child protective services reports) (Duggen et al., 1999). Data for this paper was collected through a combination of sources: maternal interviews, in home observations, pediatric records, CPS reports, health care insurer files and child developmental screens.

Similarly, widely cited RCTs of HFA programs in both Arizona and New York had mixed findings. In Arizona, statistically significant program impacts were measured in 7 out of 15 outcomes. Specifically, positive impacts were measured in reducing aggressive discipline, reducing inappropriate parental expectations, reduced oppressing [of] child's independence, increased parental safety practices, increased parental use of available outside resources, reduced parental alcohol use, and increased maternal school or training. No effects were found in reducing family violence, reducing parental lack of empathy, reducing parental belief in corporal punishment, increasing awareness of reversing roles, increased parental reading, reducing maternal emotional loneliness, increasing pathways to goals, and increasing maternal use of birth control (LeCroy & Krysik, 2011). In New York, women in the treatment group were less likely to physically abuse their children, more likely to use non-violent discipline strategies, and children displayed greater cognitive ability over the control group both at intermediate and longer term follow ups (DuMont et al., 2011).

HRSA's meta-analysis of HFA evaluated 170 studies from 1979 – 2012. HRSA found that HFA had no statistically significant positive program impacts for the majority of the studies reviewed (See Table 3). In seven out of the eight outcome domains, positive impacts were measured in approximately 10% of the studies reviewed, with the remaining 90% of the studies showing either no effect or negative/ambiguous effects. The eighth category, "Child Development and School Readiness", documented the most success across the reviewed literature, with approximately 30% of studies finding statistically significant positive program impacts for the treatment group. Several other meta-analyses of home visiting exist, but these meta-analyses are not disaggregated by program model. In other words, these meta-analyses mix data from different home visiting models and aggregates measured outcomes as evidence of home visiting's effectiveness. That approach confounds the effectiveness of each individual model in the meta-analysis because the aggregate measured outcomes do not distinguish the percentage of measured outcomes attributable to each individual home visiting model used in the meta-analysis. This paper focuses solely on HFA home visiting models in an attempt to link outcomes from the HFA home visiting program structure to observed outcomes, therefore the meta-analyses that mix program data are not included in this analysis.

While not explicitly stated in the reviewed literature, it is worth noting that participants in home visiting services could show "improvement" just through participation in a home visiting program. For example, if a mother is aware that a home visitor will be entering her home on a regular basis, she may alter her home and parenting behavior during home visits in an effort to demonstrate the behavior that she believes home visitors are looking for. This type of effect of home visiting would be undesirable, if the actual parenting that takes place outside of home visits is abusive and/or neglectful.

Hypothesis and Literature

This analysis utilizes regression techniques to estimate the slope of several program outcomes (See Table 4). Specifically, the slope of the number of home visits received will be estimated against the chosen outcomes. The hypothesis is that the relationship between the number of home visits and measured outcomes will have a correlation greater than zero, and that the coefficient on the number of home visits will be positive. If the coefficient on the number of home visits is greater than zero, this implies that additional home visits are correlated with improvements in the chosen outcomes. In other words, the Maryland MIECHV home visiting program could be viewed as effective in improving the outcomes used in this analysis if the coefficient on the number of home visits is greater than zero.

A RCT with a 15 year follow up indicated that home visits conducted for up to 2 years had increasing effects on both short and longer term outcomes, indicating that home visits and outcomes are positively correlated (Olds et al., 1997). An evaluation of a home visiting program in Jamaica found that families that received biweekly home visits had better outcomes than families that received monthly home visits (Powell & Grantham-McGregor, 1989). This analysis will determine the slope relationship between program dosage (number of home visits) and the chosen outcomes (See Table 3). In other words, what is the quantitative impact of the number of home visits on the chosen measured program outcomes? The relationship could be linear, or diminishing over time, but there is an expected positive correlation between the input (home visits) and the measured outputs at least in the short term. While this relationship has been found in the literature, it is also logical. Using the same teaching analogy, students learn more on average the more time they spend in school and the more lessons they "receive". Similarly, the more home visits received, the greater the probability that the curriculum will produce positive results on average.

Methodology

Sample

The sample contains a panel of 930 Maryland MIECHV funded families (930 female primary caregivers, 665 children) who were enrolled for at least one day in an HFA home visiting program in Maryland between January 1st, 2012 and April 7th, 2015. Family demographic information (independent variables) is collected upon enrollment. The dependent variables used in this analysis are collected at 6 month intervals, starting when the child is 6 months old. All data in this sample are collected and owned by DHMH. All observations have been de-identified by removing certain personal information in order to protect the privacy of the families in the sample. The families live in the following jurisdictions in Maryland: Baltimore City, Baltimore County, Dorchester County, Prince George's County, Somerset County, Washington County, and Wicomico County. There are a total of 13 home visiting sites represented within the 7 jurisdictions (See Table 8), however site level data was not included for Baltimore City observations.

Baltimore City HFA sites collect MIECHV data using different survey forms, therefore, some of the data points that are available for Baltimore City clients are not available for families in any of the counties, and vice versa. Most notably, county jurisdictions are not required to collect data on the number of home visits received until 12 months post enrollment, at which time many of the original members left the program. Of those that do stay in the program for at least 12 months, many families are missing this information.

Evaluating the Sample

This analysis will answer the following question:

1) What is the quantitative relationship between the number of home visits received and six dependent variables available in the dataset (see Table 4)?

The hypothesis is that the coefficient on the number of home visits is greater than zero:

H_0: coefficient on the number of home visits = 0

H_a: coefficient on the number of home visits $\neq$ 0

Table 4: **Measured outcome and dependent variable descriptions**
Note: The first number under the "Variable Name" column is the 6 month cutoff score indicating typical development. The second number is the 12 month cutoff score

Outcome	**Measurement Instrument**	**Variable Type**	**Variable Name**	**Variable(s) Description(s)**
Child cognitive development	Ages and Stages Questionnaire (ASQ-3)	Three continuous variables with cutoff scores indicating typical (above cutoff) vs. atypical (below cutoff) development	1. communication a. 29.65 b. 15.64 2. problemSolving a. 27.72 b. 27.32 3. personalsocial a. 25.34 b. 21.73	Three ASQ-3 subscale scores: 1. Communication skills 2. Problem solving skills 3. Personal-social skills Higher scores indicate greater cognitive ability
Child social emotional development	Ages and Stages Questionnaire – Social Emotional (ASQ-SE)	Continuous variable with cutoff scores indicating typical (below cutoff) vs. atypical (above cutoff) development	1. OverallScore a. 45 b. 48	1. Social Emotional Overall Subscale score. Lower scores indicate greater social emotional ability
Child physical development	Ages and Stages Questionnaire (ASQ-3)	Two continuous variables with cutoff scores indicating typical (above cutoff) vs. atypical (below cutoff) development	1. fineMotor a. 25.14 b. 34.50 2. grossMotor a. 22.25 b. 21.49	Two ASQ-3 subscale scores: 1. Fine Motor skills 2. Gross Motor Skills Higher scores indicate greater physical ability

As outlined earlier, it is reasonable to expect that the more home visits a mother and child receive, the greater the impact of the home visiting program on the chosen measured outcomes. For Baltimore City data, the number of home visits per family is available. However, as previously mentioned, for all other Maryland counties the number of home visits is not measured until 1 year post enrollment. Therefore, this analysis is restricted to families from Baltimore City.

Because all clients chose to participate in this program, the sample in this analysis is non-random. Ideally, a sample selection regression model would be utilized in an attempt to compensate for selection bias. However, the data used in this analysis do not contain observations of non-participants, so estimates of population parameters in this analysis will be biased and inconsistent (Guo & Fraser, 2014)

Sample Selection Bias

The sample utilized in this analysis is non-random; all clients were given a description of the program and voluntarily chose to enroll. This presents a situation of sample selection bias, which biases estimates of population parameters for both the participants and non-participants. The bias exists because the factors that influence whether a mother and child enroll in a home visiting program are likely correlated with the unobserved factors that influence their outcomes related to the home visiting program, and data is only available for participants. OLS could provide unbiased population estimates if 1) both participants and non-participants were included in the sample, 2) the participation decision were based entirely on the included independent variables (i.e. exogenous), and 3) the independent variables were uncorrelated with the error term (Soderbom, 2011). Unfortunately, this dataset does not meet the requirements for unbiased estimation. But this analysis can inform MIECHV program staff of outcomes achieved within this sample. This is useful in terms of retrospective evaluation, which DHMH is expected to conduct as a condition of receiving MIECHV funding. Additionally, the models in this analysis can inform future research by providing unbiased estimates given the right dataset. A dataset that contains information on both participators and non-participators is a fundamental requirement towards unbiased estimation of population parameters.

In order to control for the sample selection bias present when evaluating voluntary home visiting, the Heckman sample selection regression model would ideally be utilized, including in this analysis. If non-participant data were available, the Heckman method could yield unbiased population parameter estimates.

The first step in the Heckman model is to estimate the selection equation, which must include the variables that influence participation or non-participation. The second step is the traditional outcome equation, modeling the independent and dependent variables of interest. Without data on non-participants, dependent variable measurements are essentially truncated, and OLS regressions on truncated samples are biased and inconsistent (Soderbom, 2011) (Wooldridge, 2009).

Unfortunately, there are no straightforward predictors of participation vs. non-participation. If there were demographic predictors, for example, these could be used in a selection equation. Some factors that likely influences the decision to participate vs. not participate are not measured in these data. For example, general motivation may be the primary unmeasured predictor of participation for a mother. Mothers who are more aware of how difficult it is to provide for a child's basic and intellectual needs might be more willing to accept a home visitor. Or, for other unmeasured reasons, some mothers may feel comfortable allowing in home visits, regardless of how they view their level of preparedness for raising children. Others may simply not want a stranger in their home, regardless of their intent. In any case, the decision to participate is not clearly and entirely defined by a commonly measured variable like income or education.

Some literature has found measurable predictors of participation, but they vary across home visiting models and sites. For example, (Wagner et al., 2003) found that higher education levels and income levels were positive predictors of home visiting participation. (Olds & Kitzman, 1993) found that women were more likely to participate in any home visiting program if their children had health concerns. In future analyses, these predictors could be used in the selection equation of a sample selection model.

Endogeneity Bias

This research attempts to quantify the program dosage effect of the home visiting intervention for Maryland MIECHV HFA sites. In other words, how do outcomes change as a result of each additional home visit? While logically straightforward, the econometric analysis of this question requires an additional consideration. The number of home visits received is likely an endogenous covariate because families ultimately determine how many visits are conducted. Families can directly refuse a visit by declining scheduling attempts, or they can indirectly refuse a visit by ignoring attempts by program staff to schedule a home visit. The unobservable factors that influence the number of home visits a family chooses to receive is likely correlated with the unobservable factors that influence the variation in the dependent variables. In econometric terms, the error term is correlated with the number of home visits, violating another condition for unbiased estimation of parameters (Wooldridge, 2009).

Unlike the sample selection problem, which requires data not available in this dataset, the endogeneity problem can be addressed in this analysis by utilizing an instrumental variables approach. When families are enrolled, they are assessed for baseline risk and assigned a treatment plan through the home visiting program. Based on their level of risk, their treatment plan describes the number of visits the family should receive per month, based on the recommendation of the home visiting program model. This data point is the expected number of home visits, and it is determined entirely by the home visiting program. Therefore, expected number of home visits is used as instrument for the number of home visits, the endogenous variable. Expected number of visits satisfies the requirements of an instrumental variable, namely that it is uncorrelated with the unobserved error term, because families do not choose their expected number of visits. Unfortunately, the expected number of home visits is available only for families in Baltimore City, so families in county programs cannot be included directly in the models.

Model Descriptions

There are 6 chosen outcomes (see Table 4), for a total of 6 regressions where the independent variable of interest is the number of home visits received for observations from Baltimore City. The population relationship is assumed to have the following general form:

$$Y = \beta + \delta + \varepsilon$$

Where Y is each of the 6 dependent variables, β is the expected number of home visits (the IV for actual number of home visits), δ is a vector of control variables, and ε is the error term. The control variables must include any factors that might influence the dependent variables outside of the home visiting treatment, or the model will be biased due to omitting relevant variables. Isolating the impact of the home visiting treatment by controlling for every influence outside of home visiting, including individual level factors like motivation and parenting style, is difficult because such factors are hard to quantify accurately, if at all. Furthermore, children and mothers develop over time, with or without home visiting, so an ideal model would include data on a control group not receiving home visiting in order to establish a valid counterfactual.

This analysis will conduct three sets of regressions. This first will measure the relationship between the number of home visits and the 6 dependent variables when the child is 6 months old. This will evaluate the outcomes for children in the sample who stayed in the program until 6 months old and received 6 months worth of home visits. The second set of regressions will measure the 6 dependent variables when the child is 12 months old. This will evaluate the outcomes for children in the sample who stayed in the program until 12 months old and received 12 months worth of home visits. The third set of regressions will measure the 6 dependent variables using a panel regression with fixed effects, which will measure the effect of home visits on the 6 dependent variables for families with data available at both 6 and 12 months and account for differences within families between 6 and 12 months.

(Olds et al., 1997) controlled for marital status (married or unmarried), maternal age, maternal employment status, maternal income and whether the biological father lived in the house with the mother and child. Olds found that all five covariates were statistically significant, and therefore appropriate controls when measuring home visiting outcomes. The MIECHV data for Baltimore City has four out of the five variables used by Olds, only missing marital status. With the exception of marital status, all other Olds controls (with household income instead of maternal income) are utilized as controls in these regressions.

Ideally, a dummy variable representing all home visiting sites would be included, under the logic that the measured outcomes will vary by home visiting site. This variability across sites is consistent with the majority of the findings in the literature (Duggen et al., 1999) (DuMont et al., 2011) (LeCroy & Krysik, 2011) (Olds et al., 1997). However, due to data limitations, only families from Baltimore City are included in the sample, and the sites within Baltimore City is not known. Therefore, this analysis cannot measure site level variability. Another reason to believe that site variability exists is that not all home visitors have the same level of work experience, and not every family they are seeing has the same level of need. As the Maryland state needs assessment indicated, certain jurisdictions have more elevated indicators than other jurisdictions (DHMH, 2010), therefore it is reasonable to assume that impacts will vary across jurisdictions.

Additional controls are whether the child was born premature, whether the family has a history of child abuse or neglect, whether the family has a child or children with developmental delays or disabilities, whether the family has or had children with low student achievement, and educational attainment for the mother (see Table 6).

Table 6: Independent variables description

Variable	Description
actualhv	The actual number of home visits received
sum_exphv	The expected number of home visits based on the HFA curriculum and baseline risk
AgePrimaryCaregiver	Mothers age in years
Maternal Educational Attainment	Reference category= Less than high school, some high school, other
	HighSchool=1 if High School Diploma, GED, Vocation certificate
	College= 1 if Some College, Bachelors or Associates Degree
	EducMissing=1 if educational attainment question not answered
Household Income	overthirty = 1 Over 30k/year
	zerotosixteen=1 if 0-16k/year
	16-30k/year
	unknown income
dadliveHH	Dad lives in the household?

ChildPremature	Was the child born premature?
hist_ab_neg	Does the family have a history of child abuse and/or neglect?
lowach_devdelay	Does family have a child or children with developmental delays or disabilities? OR Does family have or had children with low student achievement?

Children who come from families with a history of abuse and neglect or developmental delays may have lower values of the dependent variables than children without such characteristics. Therefore, it is necessary to control for these family features in these models.

Results

6 month interval

The first model used in this analysis utilized a Generalized Method of Moments (GMM) Instrumental Variables regression model at the 6 month measurement interval (when the child was 6 months old) on the 6 dependent variables. The IV method was utilized on the assumption that the actual number of home visits is an endogenous covariate. The results are presented in Table 9 below. It should be noted that, with the exception of the dependent variable grossMotor1, the other 5 dependent variables were not found to be endogenous. Therefore the 5 other dependent variables utilize Ordinary Least Squares (OLS).

The regressions where communication1, personalsocial1 and OverallScore1 are the dependent variables are not jointly significant for $p<0.10$, and are therefore

Table 9: Cross sectional OLS at 6 month interval

Note: grossMotor1 regression is an IV GMM estimation, because actualhv1 is endogenous in that model. All other regressions are OLS.

	communication1^	problemSolving1	personalsocial1^	fineMotor1	grossMotor1	OverallScore1^
actualhv1	0.090	0.010	0.094	0.143	0.211	-0.104
	(0.98)	(0.10)	(0.80)	(1.46)	(1.21)	(-0.40)
ChildPremature	0.255	0.429	0.021	-0.358	-3.136	0.782
	(0.13)	(0.24)	(0.01)	(-0.19)	(-1.32)	(0.20)
College	0.539	-0.467	2.759*	-1.353	4.457**	7.034
	(0.35)	(-0.35)	(1.68)	(-0.88)	(2.46)	(0.90)
HighSchool	0.873	0.781	1.864	-1.092	2.342	0.273
	(0.68)	(0.51)	(1.25)	(-0.75)	(1.29)	(0.11)
EducMissing	2.442	3.700**	0.929	2.429	7.515***	-0.761
	(1.39)	(2.31)	(0.45)	(1.45)	(3.75)	(-0.24)
sixteenthirty	-0.883	1.270	0.019	1.620	0.192	-3.968
	(-0.65)	(0.91)	(0.01)	(1.18)	(0.10)	(-1.24)
overthirty	-2.271	1.397	-0.875	1.227	-2.095	-0.376
	(-1.05)	(0.49)	(-0.44)	(0.52)	(-0.61)	(-0.06)
dadliveHH	0.563	0.127	-0.031	-0.584	0.612	-4.561*
	(0.56)	(0.12)	(-0.03)	(-0.51)	(0.44)	(-1.79)
UnknownIncome	4.503***	4.867***	2.531	5.111***	4.033	-7.135
	(3.08)	(6.62)	(0.83)	(4.42)	(1.17)	(-1.41)
hist_ab_neg	1.304	-1.245	1.865	-2.055	0.236	1.736
	(1.04)	(-0.97)	(1.30)	(-1.47)	(0.13)	(0.51)
lowach_devdelay	-0.151	-2.037	-0.167	-0.593	-2.705	-3.015
	(-0.08)	(-0.78)	(-0.07)	(-0.31)	(-0.94)	(-1.10)
AgePrimaryCaregiver	-0.081	-0.106	-0.056	-0.038	-0.462***	0.070
	(-0.91)	(-1.17)	(-0.54)	(-0.45)	(-4.03)	(0.46)
_cons	55.056***	57.756***	53.134***	55.392***	60.394***	13.429***
	(30.88)	(31.65)	(19.61)	(28.51)	(24.12)	(2.76)
R^2	0.03	0.04	0.03	0.04	0.09	0.04
N	226	226	226	226	226	186

$p<0.1$; ** $p<0.05$; *** $p<0.01$

t-statistics in parentheses

"^" denotes that the overall test of significance was rejected and p>0 not discussed further. ProblemSolving1, fineMotor1 and grossMotor1 are jointly significant. Multicollinearity was detected in these models, but transformations of the variables did not improve the fit of the variables. Heteroskedasticity robust standard errors were utilized in response to the lack of homoskedasticity, and because the distribution of the dependent variables are not normal. Omitted variables were also detected, but it is not clear which variables (if any) from this dataset could reduce this bias.

Within the significant models, EducMissing, UnknownIncome, and College are statistically significant covariates. Notably, actualhv, the independent variable of interest, is not statistically significant at the usual significance levels. Different functional forms for this variable had a poorer fit than the simple linear version. This implies that the home visits' had no effect for families at the 6 month interval.

EducMissing and UnknownIncome have a positive effect on their respective dependent variables. These are dummy variables, so they provide a one time boost of a couple points on the dependent variable. The magnitude of the effect is more than twice as large for grossMotor1 than for problemSolving1. Unfortunately, both variables are essentially missing variables, because EducMissing represents mothers who did not answer the questions related to their educational attainment, and UnknownIncome represents mothers who did not answer the questions related to their household income. This could be interpreted as a group of the sample that values their privacy and does not wish to disclose such personal information, but there is no information in the data indicating why the fields are blank, so this line of reasoning could be no more than speculation. It is also possible that the home visitor forgot to ask the questions, or never recorded their answers. For those reasons, these education and income dummy variables offer little information on what characteristics of those observations influence the dependent variables.

Curiously, AgePrimaryCaregiver has a negative effect on the dependent variable grossMotor1, the child's gross motor skills at 6 months old. Intuition might argue that younger mothers may be associated with poorer outcomes for their children due to inexperience with parenting and relatively less maturity than older parents; however, the model does not support that argument. Each additional year of age for the mother reduces the score of the dependent variable by about 0.4 points.

The variable college has a positive effect on grossMotor1, adding roughly 4 more points to the dependent variable than the reference group which is mothers with less than a high school diploma. The effect of college is still less than the EducMissing variable, which added over 7 points to the dependent variable. The constant term is also highly significant, signaling that the value of the dependent variable is fairly accurate without any of the independent variables in the model.

12 month interval

The second set of models utilized in this analysis are cross sectional OLS on the same 6 dependent variables at the 12 month interval (when the child is 12 months old) and the variable of interest is actualhv2, which represents the actual number of home visits each family received after 12 months of enrollment in the

Table 10: Cross sectional OLS at 12 month interval

	communication2^	problemSolving2	personalsocial2^	fineMotor2	grossMotor2	OverallScore2
actualhv2	-0.027	0.071	0.123	-0.065	0.026	0.138
	(-0.26)	(0.77)	(1.27)	(-1.04)	(0.24)	(0.97)
ChildPremature	-4.479*	-8.660**	-5.720*	-4.401*	-8.269**	-5.589
	(-1.74)	(-2.07)	(-1.82)	(-1.82)	(-2.49)	(-1.18)
College	1.207	5.266*	4.944**	2.378	1.920	5.838*
	(0.43)	(1.96)	(2.10)	(0.96)	(0.69)	(1.82)
HighSchool	1.488	2.163	2.709	3.248*	0.975	9.155*
	(0.80)	(0.92)	(1.11)	(1.97)	(0.40)	(1.93)
EducMissing	4.099**	4.273*	4.109	1.589	4.615	-4.031
	(2.18)	(1.74)	(1.07)	(0.51)	(1.50)	(-1.12)
sixteenthirty	-1.728	2.497	-0.050	-1.081	1.989	-0.147
	(-0.88)	(1.02)	(-0.02)	(-0.41)	(0.74)	(-0.04)
overthirty	-5.939	0.019	-2.754	1.248	-3.352	-2.837
	(-1.24)	(0.00)	(-0.46)	(0.58)	(0.76)	(-0.49)
dadliveHH	2.300	-0.795	-3.066	-0.443	-5.192**	0.346
	(1.43)	(-0.42)	(-1.56)	(-0.34)	(-2.38)	(0.10)
UnknownIncome	5.069***	3.298	-0.477	4.893***	4.112**	7.851**
	(2.78)	(1.18)	(-0.10)	(4.39)	(2.00)	(2.21)
hist_ab_neg	1.053	-1.202	1.184	-1.962	-0.059	-3.773
	(0.52)	(-0.51)	(0.50)	(-0.75)	(-0.03)	(-1.27)
lowach_devdelay	0.115	1.553	-0.197	0.371	-4.904	-1.215
	(0.03)	(0.39)	(-0.05)	(0.15)	(-0.85)	(-0.30)
AgePrimaryCaregiver	-0.357***	-0.491***	-0.368**	-0.157	-0.515***	0.271
	(-2.83)	(-3.44)	(-2.25)	(-1.08)	(-3.27)	(1.27)
_cons	61.399***	62.092***	59.258***	58.728***	68.586***	6.675
	(16.77)	(16.62)	(14.63)	(16.50)	(17.60)	(1.18)
R^2	0.13	0.17	0.14	0.09	0.24	0.11
N	132	132	132	132	132	114

* *p*<0.1; ** *p*<0.05; *** *p*<0.01

t-statistics in parentheses

"^" denotes that the overall test of significance was rejected and p>0.1

home visiting program. An instrumental variables approach lead to the conclusion that, for all 6 regressions at the 12 month measurement period, the variable representing the actual number of home visits was exogenous. Because the actual number of visits was not endogenous, a simple OLS regression was appropriate.

The results from the OLS regressions at the 12 month measurement period are presented below in Table 10. Again, both the communication and personalsocial dependent variable regressions are not jointly significant, therefore they not discussed further.

Again, like at the 6 month measurement period, the 12 month variable measuring the actual number of home visits is not statistically significant at the usual significance levels. Again this appears to suggest that the number of home visits is not statistically different from zero. This fails to reject the null hypothesis that the coefficient on the actual number of visits is equal to zero.

Unlike at the 6 month measurement period, EducMissing is only significant for 1 of the dependent variables (problemSolving2); this dummy variable adds about 4 points to the problemSolving2 score for the child. UnknownIncome is again significant, this time for 3 out of 4 significant regressions; the magnitude ranges from roughly 4 points added to roughly 8 points added to the dependent variable. Again, both of these variables are not very useful in terms of practical significance, however, because they represent families for whom education and income information is missing.

Similar to the 6 month interval, the age of the mother is statistically significant at the 12 month interval (in 3 out of the 4 jointly significant regressions) but is negatively correlated with the dependent variable; each year of age reduces the value of the dependent.

Mothers with a college degree had a positive affect on a child's problem solving skills, adding about 5 points to their score. Oddly, having a college degree had a negative effect on a child's social emotional skills; lower scores are indicative of greater social emotional wellbeing, while higher scores are better for all other dependent variables. While a college degree added 5 points towards the child's social emotional wellbeing (a poorer outcome), a high school degree added 9 points, a worse outcome. Curiously, these findings are in addition to the reference group, those with less than a high school diploma. This is an unusual finding because one might expect greater education levels for a mother to be associated with greater social emotional capabilities for their child, but these data do not support that conclusion. More education is a statistically significant predictor of worse social emotional outcomes in this dataset.

Another curious finding is that having the biological father living in same household as the enrolled mother and her child decreased the child's gross motor functions by about 5 points. This appears to imply that, for this sample, fathers on average had a negative influence on their child's gross motor skills. One might expect that having the father in the child's life would have a positive influence, but it may be the case that some fathers are abusive and a negative influence.

Finally, premature children had the predicted effect on all dependent variables. Families with premature children had a statistically significant negative

Table 11: Panel OLS regressions with fixed effects

	communication^	problemSolving	Personalsocial^	fineMotor^	grossMotor	OverallScore^
actualhv	-0.130	-0.197*	0.008	-0.007	0.338*	0.371
	(-0.70)	(-1.71)	(0.05)	(-0.05)	(1.91)	(1.51)
_cons	54.548***	55.009***	52.636***	54.510***	50.131***	13.408***
	(51.71)	(84.59)	(57.71)	(69.47)	(50.14)	(12.18)
R2	0.01	0.02	0.00	0.00	0.05	0.01
N	358	358	358	358	358	300
sigma_u	7.4495186	9.1784292	8.3834698	7.6459403	10.577936	16.758883
sigma_e	6.5493877	7.354493	8.083891	7.0787285	7.611577	18.267122
rho	0.56403533	0.60899491	0.51818626	0.53846411	0.6588559	0.45701915

** p<0.1; ** p<0.05; *** p<0.01*

t – statistics in parentheses

Note: All covariates from the 6 and 12 month intervals were included in these panel regressions, but all are time invariant and are therefore removed.
"^" denotes that the overall test of significance was rejected and p>0.1

affect on all the significant regressions, ranging from 4.4 to 8.6 point decline in dependent variable score.

Panel Regression

The third set of models measure the effect of the change in home visits between the 6 and 12 month period on the 6 dependent variables, while controlling for individual level "within" fixed effects (See Table 11 below). This is the only set of models that detected a statistically significant effect for the variable of interest, the number of home visits received. Statistical significance for the variable of interest was found in the only 2 regressions that were jointly significant: problemSolving and grossMotor. Curiously, the coefficient on actualhv is negative in the problemSolving regression, implying that the average impact of each visit from 6 to 12 months reduced the child's problem solving score by about 0.19 points. This appears counterintuitive, but it should be noted that the magnitude of this effect is fairly small: it would take 5 home visits to reduce problem solving skills by 1 point, and 5 visits consists of at least a month if not 2 months worth of visits per family. Gross motor skills are affected by home visits in the way initially predicted; each home visit increases gross motor score by about 0.34 points, which translates to roughly 3 visits for a 1 point increase. Like with problem solving, the magnitude of this coefficient is small. It should be noted that the average values of both significant dependent variables (the constant term) is already a large value in comparison to the cutoff scores indicating typical child development for each dependent variable (See Table 4). Another interesting feature of both significant regressions in this set of models is that the percentage of the variance that is due to individual level fixed (see rho in Table 11 above) effects is high, roughly 61% for problemSolving and 66% for grossMotor. This implies that individual level effects have a strong influence on the dependent variables, a feature that supports that idea that there are many factors not measured in these data that affect the dependent variables.

Beyond actual number of home visits received, this analysis did not find many of the other regressors statistically significant. These regressors were compared to the same regressors for the county jurisdictions in an effort to use the county data. Recall that the county data could not be used because no data was collected on the actual number of home visits until 12 months post enrollment, and most families who made it to the 12 month milestone were missing that data. This analysis compared the value of the coefficients of the regressors utilized in the 18 regressions for the county through a chow test. The chow test revealed that the additional regressors were statistically the same as the Baltimore City regressors. The caveat is that, because actual home visits were not available, the chow test was done with time enrolled in the program, an imperfect proxy for the actual number of home visits received. It should also be noted that, while the coefficients of the regressors in the city and counties were found to be similar, many of these regressors were not significant in the City, and therefore are not significant in the counties.

Analysis

This analysis utilized three models, two cross-sectional and one panel regression, in an attempt to estimate the affect of each home visit on the set of dependent variables that measure a range of children's development. The hypothesis was that the coefficient on the number of home visits would not be equal to zero, with an intuition that it would likely be greater than zero. The null hypothesis that the coefficient was equal to zero was not rejected for the vast majority of the regressions. There were 6 regressions for each of the 6 dependent variables run at the 6 and 12 month intervals, and a panel regression, for a total of 18 regressions. Out of the 18 regressions, only 2 found the actual number of home visits to be statistically significant. One of those regressions found that home visits had a negative effect on problem solving. The sole regression that had a statistically significant positive effect was the panel regression on gross motor skills, where each home visit added approximately 0.34 points to the gross motor value. Table 3 in the Appendix indicates that HRSA's meta-analysis of HFA programs revealed that 11 studies found positive effects for child development and school readiness, while 37 studies showed no effect, and 0 found a negative effect. These findings indicate that, out of 18 regressions at various intervals, 16 regressions found no effect, 1 regression found a positive effect, and 1 found a negative effect. It should be noted, however, that for all 18 regressions, the average value of the dependent variables without any of the regressors in these models were well above the cutoff scores indicating typical child development (See Table 4). To further emphasize an important qualification about these findings, the coefficients and significance of the models in this analysis are only applicable to this sample due to selection bias. Additionally, there was omitted variables bias detected in virtually all of the cross sectional regressions, which is further evidence that key factors influencing these dependent variables are not measured in this dataset.

There are many possible explanations for why the data revealed no significant relationship between the number of home visits and the dependent variables. The first possibility is that the HFA home visiting programs with families in this sample do not affect the dependent variables. In other words, for the families in this sample, the HFA program has no effect on child development and school readiness. This conclusion is based only on the results of the 18 regressions in this analysis, and is reasonable because the coefficient on the number of home visits was not significant in 16 out of 18 regressions, and one regression found a negative impact.

A second possibility is that the dependent variables in this analysis do not accurately measure what they claim to measure, namely, child communication, problem solving, personal social, fine motor, gross motor, and social emotional skills and wellbeing. The authors of the Ages and Stages Questionnaire, the survey instrument that calculates the values of these dependent variables, claim that their assessment tools are reliable and valid (Paul H. Brookes Publishing Co., 2015). This does not necessarily mean that there is no measurement error between the actual skills involved in each dependent variable and the values of the dependent variables. Parents answer roughly 5 questions with a “Yes”, “Sometimes” or “Not

Yet" for each subscale, and a final score is calculated from those responses. Practically, it is reasonable to doubt that 5 questions and with a simple 3 choice response could accurately measure a child's skills in any of the subscale areas without error. Furthermore, because the questions about the children are asked of their parents, the responses given by the parents are subjective. Parents are typically the caregiver that spends the most time with the child, and know more than others could about their child's development, but this does not remove the possibility of exaggeration or misinterpretation of their child's ability. If there were measurement error either through the inaccuracy of the assessment tool or the inaccurate interpretation of the child's abilities by their parents, this would bias the estimates of the coefficients in this model further (in addition to the omitted variables bias). Furthermore, assuming measurement error, if the true value of the dependent variables follow a different sampling distribution than the ones in this sample, the hypothesis tests indicating statistical significance in this analysis would be invalid.

A third possibility to explain the findings is that the first measurement period is too late in the child's life to accurately capture the effect of the home visiting program on the families. Children's development is rapid during the first months of life, and these data capture a measurement of the dependent variable for the first time at 6 months old. Considering almost every client is enrolled in a Maryland MIECHV program before 1 month old (and in most cases very close to birth or prenatal enrollment), measuring the dependent variable at 6 months old does not capture the effect of the home visiting program from birth through 6 months. In other words, without baseline measurements for these children, one can only speculate regarding the effects of the home visiting program prior to the 6 month measurement period. It may be the case that most of the children entering the program were at significant risk and the home visiting program increased their scores on the dependent variables considerably between birth and 6 months old. But without baseline data, it is also possible that all of these children were born to highly motivated parents who improved their child's circumstances on their own, and never needed home visiting. Neither story can be verified without baseline data.

Another optimistic possibility is that the benefits of home visiting do not appear in these dependent variables, but benefits do appear in other ways and only later in life. It may be the case that the benefits of home visiting do not materialize in measurable ways until the child is in elementary, middle or high school, and potentially into adulthood. As indicated in the literature review, some research has found adverse consequences of child abuse and neglect through child and adulthood, so it may be reasonable to expect that there are benefits from home visiting that do not materialize until later in life, and that these benefits may be difficult to measure. Examples might be a lower probability for mental illness, or higher educational attainment and achievement than if an individual had not received home visitation services.

Conclusions and Recommendations

The conclusions of this analysis are limited by the dataset. Without data on non-participants, this analysis is not generalizable to the general population, which is the ultimate goal of this type of analysis. Additionally, with omitted variables bias due to a lack of measureable data points that represent the dependent variables, these regressions contain biased estimates. Therefore, the primary recommendation is to collect more data that might accurately serve as variables that measure some factors certain to affect home visiting that are not currently in the dataset, such as general motivation levels and attitudes towards parenting and life.

With an unbiased estimate of population parameters, home visiting program staff could estimate the number of home visits necessary to improve a baseline score to a desired level. However, that type of system requires baseline measurements, which this dataset does not have. Therefore it is recommended that program staff measure outcomes as close to baseline as possible, not only for these dependent variables but also for those related to the mother. This includes not only a baseline level of risk (which Baltimore City has with it's service level variable) but the actual needs of the family. Some enrolled families may need home visiting services primarily for the mother, while other families' children may need more attention, and other families might need everything the program offers. Without information on what specific family circumstances the home visiting service is attempting to improve, models like those used in this analysis may conclude that the program had no effect when it never intended to move certain outcomes in the first place. Starting with improving the collection of baseline measurements, the Ages and Stages Questionnaire offers assessment tools for children as young as 2 months old, and there may be additional options available as assessment tools that may have less potential for measurement error. Program staff should consider capturing the values of these dependent variables on the 2 month ASQ intervals in order to estimate baseline scores.

Another significant limitation in this analysis is that a couple of the statistically significant variables across several models do not provide useful information to stakeholders due to missing data. Both the educational attainment variable "EducMissing" and the household income variable "UnknownIncome" were significant but provide little useful information for stakeholders. This is because these families did not have information in the dataset for their income or education, leaving one to wonder what about those particular families was influential. Home visiting program staff should strive to enter relevant data whenever possible in order to provide more accurate information on what factors influence these outcomes.

Like Baltimore City, county jurisdictions receiving MIECHV funds should collect information on the number of home visits received on a more regular basis – Baltimore city home visiting sites collect this data monthly. Waiting until 12 months post enrollment neglects to count the impact of home visits prior to 12 months in the program, at which point there is attrition. Additionally, this data point at 12 months post enrollment is missing for the majority of clients who achieve this milestone.

Finally, it is entirely possible that home visiting is not an effective intervention, as found in this dataset. However, it is also likely that the dependent variables contain measurement error and that some of the factors (independent variables) influencing the dependent variables are not in this dataset and are difficult to measure in general. Future research should strive to utilize a rich dataset that contains significantly more information on both participants and non-participants so that estimations can be as accurate as possible. Until the relationships between initial risk, the content of that risk, baseline scores, and follow up measurements are collected in a dataset, estimation results will continue to be less than ideal because they don't measure all the important factors that influence families and home visiting.

Appendix

Table 2: HFA Critical Elements required for model fidelity

Element Number	Element Description
1	“Initiate services prenatally or at birth”
2	“Use a standardized (i.e., consistent for all families) assessment tool to systematically identify families who are most in need of services. This tool should assess the presence of various factors associated with increased risk for child maltreatment or other poor childhood outcomes (i.e., social isolation, substance abuse and parental history of abuse in childhood)”
3	“Offer services voluntarily and use positive, persistent outreach efforts to build family trust”
4	“Offer services intensively (i.e., at least once a week) with well-defined criteria for increasing or decreasing intensity of service and over the long term (i.e., three to five years)”
5	“Services should be culturally competent such that the staff understands, acknowledges, and respects cultural differences among participants; and materials used should reflect the cultural, linguistic, geographic, racial, and ethnic diversity of the population served”
6	“Services should focus on supporting the parent(s) as well as supporting parent-child interaction and child development”
7	“At a minimum, all families should be linked to a medical provider to assure optimal health and development (e.g., timely immunizations, well-child care, etc.) Depending on the family’s needs, they may also be linked to additional services such as financial, food, and housing assistance programs, school readiness programs, child care, job training programs, family support centers, substance abuse treatment programs, and domestic violence shelter”
8	“Services should be provided by staff with limited caseloads to assure that home visitors have an adequate amount of time to spend with each family to meet their unique and varying needs and to plan for future activities (i.e., for most communities no more than 15 families per home visitor on the most intense service level. For some communities the number may need to be significantly lower e.g., less than 10)”
9	“Service providers should be selected because of their personal characteristics (i.e., nonjudgmental,

	compassionate, able to establish a trusting relationship, etc.), their willingness to work in or their experience working with culturally diverse communities, and their skills to do the job”
10	“Service providers should have a framework, based on education or experience, for handling the variety of experiences they may encounter when working with at-risk families. All service providers should receive basic training in areas such as cultural competency, substance abuse, reporting child abuse, domestic violence, drug-exposed infants, and services in their community”
11	“Service providers should receive intensive training specific to their role to understand the essential components of family assessment and home visitation (i.e., identifying at-risk families, completing a standardized risk assessment, offering services and making referrals, promoting use of preventive health care, securing medical homes, emphasizing the importance of immunization, utilizing creative outreach efforts, establishing and maintaining trust with families, building on family strengths, developing an individual family support plan, observing parent-child interactions, determining safety of the home, teaching parent-child interaction, managing crisis situations, etc.)”
12	“Service providers should receive ongoing, effective supervision so that they are able to develop realistic and effective plans to empower families to meet their objectives; to understand why a family may not be making progress and how to work with the family more effectively; and to express their concerns and frustrations”

Source: (Healthy Families America, 2015)

Table 3: HFA - Number of studies with favorable, no effect, or unfavorable/ambiguous program outcomes for participants, by HRSA outcome domain

Outcome Domain	Favorable	No Effect	Unfavorable or Ambiguous
Child Development and School Readiness	11	37	0
Child Health	4	40	1
Family Economic Self-Sufficiency	3	37	2
Linkages and Referrals	1	16	1
Maternal Health	3	69	0
Positive Parenting Practices	6	83	0
Reductions in Child Maltreatment	15	142	0
Reductions in Juvenile Delinquency, Family Violence, and Crime	1	29	0

Source: HRSA

Table 5a: Summary statistics of dependent variables for Baltimore City

VARIABLES	(1) N	(2) mean	(3) sd	(4) min	(5) max
communication1	118	54.44915	6.497333	35	60
grossMotor1	118	51.65254	9.872155	10	60
fineMotor1	118	54.95763	7.912334	15	60
problemSolving1	118	56.10169	8.246615	0	60
personalsocial1	117	53.97436	7.783118	25	60
OverallScore1	82	17.5	31.32122	0	270
communication2	74	51.82432	11.63292	10	60
grossMotor2	74	53.37838	11.58968	15	60
fineMotor2	74	54.93243	6.9486	35	60
problemSolving2	74	51.21622	11.2813	10	60
personalsocial2	74	51.68919	11.26508	15	60
OverallScore2	49	21.10204	23.33028	0	150

Notes: Variables are ASQ subscales. Each variable with a “1” was measured at 6 months postpartum. Each variable with a “2” was measured at 12 months postpartum.

Table 5b: Summary statistics of dependent variables for the counties

VARIABLES	(1) N	(2) mean	(3) sd	(4) min	(5) max
communication1	137	53.79562	7.162134	15	60
grossMotor1	137	51.35036	9.692016	15	60
fineMotor1	137	53.94161	7.93889	25	60
problemSolving1	137	55.58394	7.50161	20	70
personalsocial1	137	53.17518	8.442625	20	60
OverallScore1	127	13.66142	22.24903	0	220
communication2	76	54.47368	6.24921	40	60
grossMotor2	76	53.42105	10.96086	10	60
fineMotor2	76	55.32895	8.730618	0	60
problemSolving2	76	51.38158	9.223112	25	60
personalsocial2	76	50.26316	10.42096	20	60
OverallScore2	79	14.11392	13.12561	0	70

Notes: Variables are ASQ subscales. Each variable with a “1” was measured at 6 months postpartum. Each variable with a “2” was measured at 12 months postpartum

Table 7b: Descriptive Statistics for Independent Variables for Baltimore City

VARIABLES	(1) N	(2) mean	(3) sd	(4) min	(5) max
actualhv1	526	6.705323	5.474673	0	24
actualhv2	526	11.3365	10.0243	0	45
sum_exphv1	524	14.9084	6.776007	0	24
sum_exphv2	524	24.96819	14.05087	0	48
ChildPremature	294	0.1462585	0.3539677	0	1
College*	526	0.1920152	0.3942599	0	1
HighSchool*	526	0.3707224	0.483458	0	1
EducMissing*	526	0.0893536	0.285525	0	1
sixteenthirty**	526	0.0855513	0.2799666	0	1
overthirty**	526	0.0190114	0.1366949	0	1
dadliveHH	526	0.28327	0.4510153	0	1
UnknownIncome**	526	0.0798479	0.2713156	0	1
hist_ab_neg	526	0.0152091	0.1225004	0	1
lowach_devdelay	526	0.1064639	0.308724	0	1
AgePrimaryCaregiver	525	26.83323	5.859831	15.57534	0.24384

"*" represents all observations' educational attainment, with "educmissing" representing the percentage of observations where education is missing.
"**" represents all observations' household income levels including cash benefits, with UnknownIncome representing the percentage of observations where education is missing.

Table 7b: Descriptive Statistics for Independent Variables for the counties

VARIABLES	(1) N	(2) mean	(3) sd	(4) min	(5) max
MarriedorCohab	405	0.143	0.351	0	1
College*	405	0.178	0.383	0	1
HighSchool*	405	0.235	0.424	0	1
LessHighSchool*	405	0.358	0.480	0	1
EducMissing*	405	0.244	0.430	0	1
Zerotosixteen**	405	0.751	0.433	0	1
Sixteenthirty**	405	0.141	0.348	0	1
Overthirty**	405	0.0494	0.217	0	1
UnknownIncome**	405	0.0593	0.236	0	1
otheradultsHH	405	0.444	0.498	0	1
dadliveHH	405	0.405	0.491	0	1
BaltimoreCounty^	405	0.0543	0.227	0	1
BrBeg^	405	0.128	0.335	0	1
ChResCent^	405	0.173	0.379	0	1
DorchesterCounty^	405	0.198	0.399	0	1
MaryCent^	405	0.0593	0.236	0	1
SomersetCounty^	405	0.0765	0.266	0	1
WashingtonCounty^	405	0.178	0.383	0	1
WicomicoCounty^	405	0.133	0.340	0	1
ChildPremature^	405	0.0198	0.139	0	1
TimeEnrolledPrimaryCaregiver	405	269.9	240.4	0	986
AgePrimaryCaregiver	405	25.10	5.701	14.51	55.89
ChildAgeTC	293	69.21	42.81	1	172.3
hist_ab_neg	405	0.158	0.365	0	1
lowach_devdelay	405	0.0642	0.245	0	1

"*" represents all observations' educational attainment, with "educmissing" representing the percentage of observations where education is missing.
"**" represents all observations' household income levels including cash benefits, with UnknownIncome representing the percentage of observations where education is missing.
"^" represents a home visiting site within a jurisdiction.

Table 8: Jurisdictions and corresponding sites

Jurisdiction	Site	Primary Caregivers (Mother)	Children
Baltimore City	Site level data unavailable	525	372
Baltimore County	Baltimore County HFA	22	11
Dorchester County	Dorchester County HFA	80	63
Somerset County	Somerset County HFA	31	24
Prince George's County	Bright Beginnings	52	25
	Child Resource Center	70	63
	Mary's Center	24	16
Washington County	Washington County HFA	72	53
Wicomico County	Wicomico County HFA	54	38
Totals		930	665

Source: Authors calculations.
Note: Numbers represent clients enrolled for at least 1 day from 1/1/2012 to 4/7/2015.

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